Times Series Momentum
Theory and Practice

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Declaration

This this is my own work and has not been submitted for another degree, either at University College, Cork or elsewhere.

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Chapter One

Time Series Momentum: An Overview

1. Time Series Momentum

1.1 Introduction

Trend following investing, the strategy of buying recent winners and selling (or shorting) recent losers, has long been a significant component of the decision making processes of many investors, both professional and private. While a wide variety of methodologies are used to capture the effect, all rely on the assumption of a continuation in price returns, or, put alternatively, that there is a positive relationship between past and future price returns. A recent paper (Moskowitz *et al.* (2012)) terms the effect time series momentum and provides a formal definition from an academic perspective.

This investigation of time series momentum has its origins in an observation made in early 2013. Commodity trading advisors (CTAs), generally assumed to run trend following investment strategies, received a significant inflow of assets following large positive returns in 2008. However, performance since then had been below the long term average. In the twenty-nine years from 1980 to 2008, the BarclayHedge CTA Index generated an average return of 12.2% per annum and only had three years with a negative return, while of the following four years to 2012, three had negative returns. The divergence becomes even more striking when compared to the long run performance of trend following, illustrated in Figure 1.1. The cumulative return of time series momentum in the period from 1950 to 2012, Panel A, shows significant positive excess return with few periods of negative or even flat returns[1]. In contrast, Panel B shows that collectively, CTA funds failed to produce any return over the four years between 2009 and 2012.

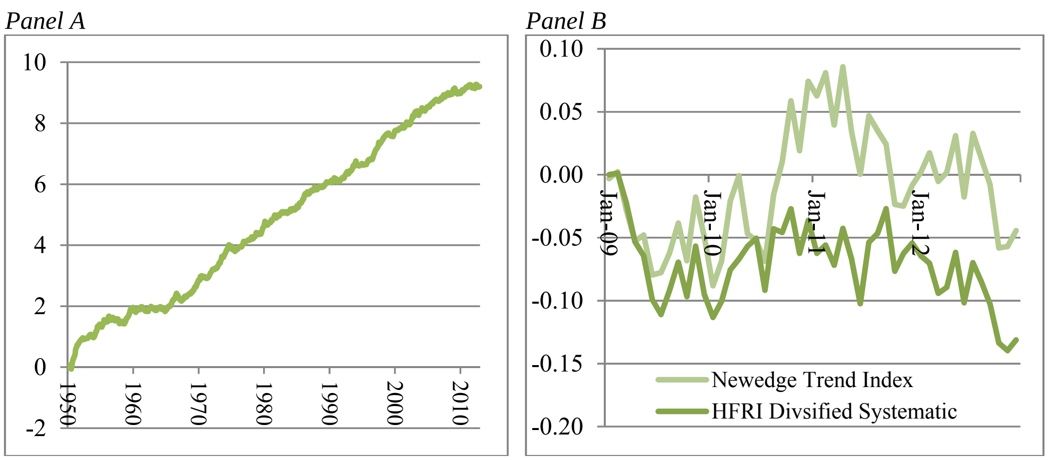
Unsurprisingly, the divergence between long-term and more recent performance led to uncertainty over the future prospects of the strategy. In particular, investors focused on whether the future performance would more closely resemble the poor performance of the previous four years or the long term average. The observation that the poor performance corresponded to the largest financial crisis since the Great Depression led to another hypothesis, that rather than being atypical, the poor performance was normal for the strategy in times of financial crisis and as markets reverted to normal behaviour

[1] The results shown here are consistent with other long term assessments of time series momentum, including Hurst *et al.* (2012) and Lempérière *et al.* (2014).

following the crisis, the performance of time series momentum would return to its typical long term values.

Figure 1.1
Cumulative Performance of Time Series Momentum

The figure shows the cumulative return of time series momentum based strategies over the long and short term. Panel A shows the natural log of the cumulative return of a simulated diversified portfolio generated with a time series momentum trading strategy from January 1950 to December 2012. Panel B shows the natural log of the cumulative return of two leading trend following CTA indices over the four year period from January 2009 to December 2012.



Source: Hutchinson and O'Brien (2015)

Source: Newedge, Hedge Fund Research

The investigation highlighted that while the strategy was extensively used in industry, time series momentum is underrepresented in academic literature. Much of the available work shows that the strategy has generated returns significantly above the risk free rate. While evidence that information from past price history could predict future price movements is, *prima facie*, an anomaly to the efficient market hypothesis, the potential anomaly has received far less attention in the literature than others.

1.2 Time Series Momentum

Trading based on continuations in price movement has a long history in the finance industry. Charles Dow emphasises the importance of trend when setting out what was to become Dow Theory at the turn of the twentieth century (Bishop (1961)) and aspects of the strategy can be traced back even further to candlestick analysis, developed for rice trading in 18th century Japan (Caginalp and Laurent (1998)). More recently, surveys have consistently shown that technical trading strategies, of which trend following is a core component, are not only a significant part of the investment processes of both professional and individual investors across financial markets but are often given more weight than fundamental analysis (Lukac *et al.* (1988a) and Menkhoff and Taylor (2007)). The performance of CTAs (Fung and Hsieh (2001)) and currency traders (Pojarliev and Levich (2008)) has been shown to be closely related to the return of trend following strategies. This wide spread use of trend following techniques is not of itself evidence that time series momentum can form the basis of a profitable trading strategy but it does provide motivation for detailed study of the phenomenon.

The literature investigating time series momentum is limited, much of the work has focused on simple performance tests, looking at the return generated by time series momentum based trading strategies, generally relative to the risk free rate. The preponderance of evidence confirms the excess performance of the strategy[2].

Despite this, there is little literature focused on explaining an apparent anomaly to the efficient market hypothesis. Academic debate on the hypothesis has focused almost exclusively on equity markets (see, for example, Fama (1991) and Malkiel (2003) who highlight the key issues from an efficient market hypothesis perspective and Barberis and Thaler (2003) who present a behavioural overview). While there have been a number of efforts to explain the returns as risk premia (Fung and Hsieh (2001) make a key contribution) or through other market mechanisms (see, for example, LeBaron (1999)), the literature remains incomplete.

1.2.1 Commodity Trading Advisors

The industry sector most closely associated with trend following strategies is managed futures where commodity trading advisors (CTAs) are generally assumed to run trend following strategies. Testing this assumption, Fung and Hsieh (1997) show trend-following is the dominant self-described strategy and the same authors show (Fung and Hsieh (2001)) that despite the variation in individual CTA returns, trend following is the single dominant component.

CTAs have become a significant part of portfolios of institutional investors. Figure 1.2 shows the growth in assets under management, which reached 334bn USD by the first quarter of 2016. A detailed analysis of the risks and returns to time series momentum investing is essential to these investors to fully understand their allocation to CTAs.

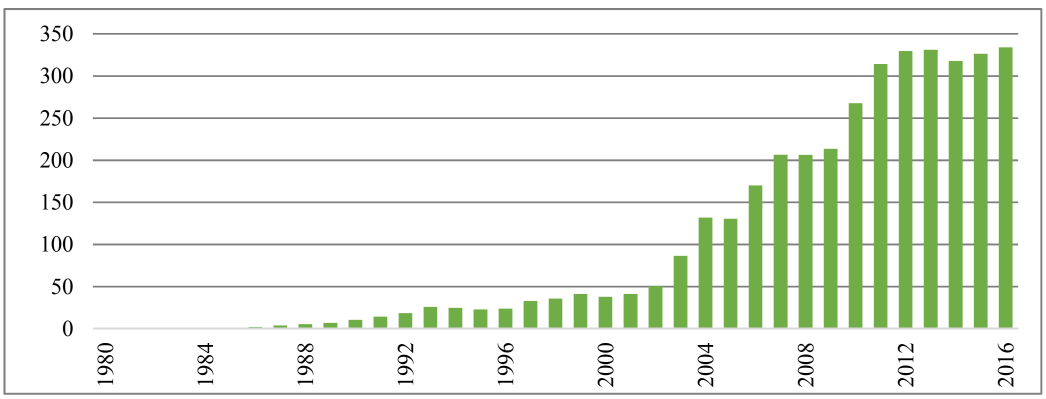
[2] This will be extensively discussed in the next chapter

However, the reverse is also true, analysis of the returns of CTAs can be used to support evidence generated from statistical analysis of price data and simulated portfolios. As the performance of CTAs includes all transaction costs and represents out of sample tests of trading strategies, evidence of positive CTA returns can be used to counter two of the most common explanations of anomalous results; profits are not available after properly incorporating costs and apparent profits are the result of data mining.

The other key group associated with trend following is foreign exchange dealers, who use trend based indicators as one class in a range of technical analysis techniques (Menkhoff and Taylor (2007)). The performance of currency managers is less relevant to this study as, by focusing on only one asset class, it provides a smaller research sample and trend following is not the dominant style, particularly at horizons beyond one month (see, for example, Cheung *et al.* (2004) and Gehrig and Menkhoff (2004)).

Figure 1.2
CTA Industry – Assets Under Management: 1980-2016

The table shows the assets under management in the CTA industry, reported by BarclayHedge. The numbers are presented in billions of USD. All figures represent year end, except 2016, which is dated to the end of the first quarter. The AUM were 310 million USD in 1980 and first exceeded one billion USD in 1984.



Source: BarclayHedge

1.3 Report Structure

The research is presented in six further chapters. The next chapter reviews the literature, to identify the current understanding of time series momentum and the appropriate framework for its analysis. The research is presented as three self-contained research papers, each making up one of the following three chapters. This is followed by a chapter investigating the robustness of assumptions implicit in the research papers. The report finishes with a chapter drawing together the main conclusion of the three papers in a unified structure. The content is laid out below.

Time Series Momentum: Theory & Evidence: The current academic evidence on time series momentum is assessed. The chapter starts with a discussion of the efficient market hypothesis and arbitrage pricing theory. These form the central framework for analysing investment returns in general and time series momentum in this research program. This is followed by a survey of the evidence on the performance profiles series momentum trading strategies and CTAs. The explanations for the excess return are then reviewed. The chapter concludes with a discussion of behavioural finance as a key alternative to the efficient market hypothesis.

Is This Time Different? Trend-Following and Financial Crises: This paper explores the divergence between typical long run performance and the poor performance highlighted from 2009 to 2013, testing whether this is typical of trend-following strategies in periods of financial crisis. The return series of diversified and asset class specific portfolios, constructed from time series momentum signals, are generated over the period from1925 to 2013. Financial crises in this period are identified and differences in return characteristics between crisis and normal periods presented. The tests are repeated on a set of regional crises to confirm earlier results. Finally, the price structure of the futures' market is analysed in crisis and non-crisis periods to help explain the divergent performance of time series momentum.

Time Series Momentum and Macroeconomic Risk: The paper investigates the relationship between time series momentum and economic conditions. It focuses on the period 1950, when monthly economic data first becomes available, to 2014. The link between performance and, first, the economic cycle and then, economic variables is investigated. Both linear and conditional relationships are considered. The returns to time series momentum are decomposed into components based on economic factor related and idiosyncratic asset returns. Finally, a recently developed measure of economic uncertainty is used to investigate the relationship between time series momentum and macroeconomic risk.

Just a One Trick Pony? An Analysis of CTA Risk and Return: The focus of the research moves to CTAs and the performance of these funds is analysed based on the constituents of the BarclayHedge CTA database. A bias free database is used to measure the performance of CTAs from 1987 to 2015. Using both cluster analysis and self-classification, the assertion that CTAs are a homogenous group employing time series momentum based trading strategies is tested. A variety of alternative risk premia are used to categorise the trading strategies of the different groupings and to measure the extent the performances can be explained by risk premia.

Robustness: The work concludes with an investigation of the robustness of three assumptions implicit in the previous work and in the literature in general. The validity of basing conclusions on synthetic futures prices rather than exchange traded data is tested. The transaction cost model used in the papers is verified. Finally, the fee structure of CTAs is examined, in particular the assumption of a standard structure comprising of a 2% management fee and 20% incentive fee is tested.

Conclusion: The final chapter unifies the conclusions reached in the previous three papers into a single theme. It finishes by highlighting areas requiring further research.

1.4 Key Contributions

The research program set out to extend the literature on time series momentum and each paper makes a number of contributions, set out below.

Is This Time Different? Trend Following and Financial Crises

This is the first peer reviewed paper to generate a performance series for time series momentum back to 1925. Further the paper shows the returns, generated from an internationally diversified, multi asset class portfolio are statistically significantly above the risk free rate over the period even after the deduction of management fees. It provides direct evidence on the performance of the strategy during financial crises, demonstrating the link between below average performance of time series momentum strategies and financial crises. Finally, the paper identifies structural changes in futures markets between crisis and non-crisis periods, providing an explanation for the poor performance of time series momentum in crisis periods.

Time Series Momentum and Macroeconomic Risk

The paper provides evidence that time series momentum portfolio returns exhibit statistically significant differences across the business cycle. The performance is shown to be higher in economic expansions than recessions, although on average positive in both. Second, it demonstrates that though a linear macroeconomic factor model has little explanatory power, a model which allows the coefficients to vary through time, does result in several of the macroeconomic factors having a statistically significant relationship with time series momentum. The paper decomposes the returns of time series momentum portfolios based on economic factor-related or asset-specific portions of price returns. It shows that both portions generate statistically significant returns and that the returns generated by the economic factor related portfolio account for about 40% of total returns. Finally, using a new estimation approach for the measurement of economic uncertainty, a negative relationship between the performance of time series momentum and economic uncertainty is demonstrated.

Just a One Trick Pony? An Analysis of CTA Risk and Return

The paper develops and uses a novel approach to create the largest backfill free CTA dataset in the literature. The time period for accurate estimates of historical performance of the industry is extended back to 1987 and the statistically significant excess performance of CTAs back to that date is demonstrated. This is the first study to unify contemporary global asset pricing based risk factors with a CTA database to examine risk attribution and performance. Utilising clustering techniques, eight different styles of CTA were identified, each with different risk attributes. Analysis of the clusters showed that while the time series momentum factor was the dominant strategy in CTAs, a number of the clusters did not have any exposure to time series momentum. Finally, evidence is presented to show that exposure to alternative risk factors explains a relatively small proportion of differences in CTA fund returns, casting doubt on the use of low cost alternative beta products to capture the returns of this sector.

1.5 Notes

1.5.1 Terminology

There is some variation across the literature in the terminology used to describe time series momentum. The term trend-following is generally used within the finance industry to refer to the trading strategy, while both time series momentum (Moskowitz *et al.* (2012) claim to be the first to use this term) and trend-following are used in the academic literature. The two terms are used synonymously in this work. The term momentum is generally accepted to refer to cross-sectional momentum. This is the market neutral strategy of buying relative winners and shorting relative losers. This strategy is related to but distinct from time series momentum. However, the term is occasionally used to refer to time series momentum, rare in academic literature but more common in industry. In this work momentum always refers to cross-sectional momentum.

Commodities has a broad and narrow meaning within the literature. In the widest definition the term can encompass any futures contract trading on an exchange. However, the narrow meaning is preferred here where the term commodity refers to future contracts based on physical products (typically agricultural products, metals and energy) but excludes futures based on financial products (equities indices, government bonds and currencies).

It is common across the literature to divide the futures universe into four sub-classes, equity indices, government bonds, currencies and commodities and analyse these separately. Where this work refers to four asset classes or standard asset classes, it refers to this specific division. In the few cases where an alternative division arising in the literature is discussed, the classes are referred to specifically.

1.5.2 Formatting

The content of the three papers, presented in chapters three, four and five, matches exactly the published or latest version. However, in order to maintain a consistent presentation through-out a number of changes were made in the layout and referencing. A single unified bibliography provided with the individual bibliographies removed. The numbering of sections, tables and figures is updated to allow consistent referencing. Finally, a number of tables and figures were reformatted to better fit the layout of this document. An extra appendix, including addition material to the published paper, is added to chapter three.

Chapter Two

Time Series Momentum: Theory and Evidence

2. Time Series Momentum: Theory & Evidence

This chapter describes the current literature on time series momentum and issues related to its study. The research that forms the basis of this work is presented as three papers, each with a literature review specific to its individual research focus. In order to minimise repetition, this review will focus on areas not covered in the individual reviews. It is divided into five sections, designed to provide a background to and context for the research carried out for the thesis.

Efficient Market Hypothesis: The efficient market hypothesis and the related pricing models are discussed first. Collectively, these provides the framework for much of the analysis in the following chapters, as well as in the literature in general. In addition, early tests of the random walk model are closely linked with tests for time series autocorrelation.

The Performance of Time Series Momentum: This section focuses on reviewing the evidence presented in the literature on the presence of time series momentum in financial markets and related effects, in particular, whether time series momentum can provide the basis for investment strategies generating returns in excess of the risk free rate. In addition, by taking a chronological approach to the evidence, it also tracks the evolution of the methods used to capture time series momentum.

Commodity Trading Advisors: The performance of CTAs, generally assumed to run time series momentum strategies, is analysed to supplement the evidence presented in the previous section, again focusing on performance measured in excess of the risk free rate. The biases inherent in extracting aggregate return statistics from databases are highlighted.

The Theory of Time Series Momentum: The explanation of the excess returns is considered here, focusing on risk based explanations, including the development of risk factors. Efforts to explain the return by exposure to traditional pricing factors is first discussed. This is followed by an examination of the development of alternative risk premia and the section concludes with a review of efforts to link the performance of investment strategies to the economy.

Behavioural Finance: The chapter finishes with a brief review of behavioural finance. Although the links between time series momentum and behavioural biases have not been explored yet, many of the models proposed by theorists attempt to explain price continuations in other contexts, notably cross-sectional momentum in equity markets.

2.1 Efficient Market Hypothesis

In general terms, an efficient market is one in which prices "*fully reflect*" all available information (Fama (1970)). Jensen (1978) provides a more formal definition:

"A market is efficient with respect to information set θ_t, if it is impossible to make economic profits by trading on the basis of information set θ_t."

The concept has a long history in the study of financial markets. Courtault *et al.* (2000) trace its origins back to Bachalier's *Theorie de la Speculation*, published in 1900. Bachalier finds security prices on the Paris bourse can be modelled using a random walk and, consequently, "*the expectation of the speculator is zero*".

Working (1934) is generally credited with highlighting the random walk model of price returns in the academic literature. Kendall and Hill (1953) produce an early rigorous test, their analysis, based on the movement of aggregate prices by industry, finds no evidence of autocorrelation. Osborne (1959) also finds that price movements on the New York Stock exchange are random, although he suggests they are better characterised by a log-normal distribution. A series of papers, including Samuelson (1965) and Fama and Blume (1966), fail to find evidence of violations of the random walk model in market data.

In *Efficient Capital Markets,* Fama (1970) provides a synthesis of the research up to that time. The author defines an efficient market as one "*in which prices always fully reflect available information*" and sets out three forms of the hypothesis; weak, semi-strong and strong. The author later associates each form of the hypothesis with an set of tests (Fama (1991)), outlined in Table 2.1.

As it is defined fully from past prices, time series momentum is linked to the weak form of the hypothesis. The hypothesis presents a theoretical barrier to trend based strategies generating an excess return, while evidence of excess return, absent a risk based explanation, provides a challenge to the hypothesis.

Table 2.1
The Forms of the Efficient Market Hypothesis

The table list the three forms of the efficient market hypothesis, along with the relevant information set, (Fama (1970)) and the appropriate tests (Fama (1991)).

Form	Information Set	Test
Weak	Past price history	Return predictability
Semi-Strong	All publically available information	Event studies
Strong	All public and private information	Private information

The standard pricing model for tests of the efficient market hypothesis, still widely used, is the capital asset pricing model (CAPM). This was developed by Sharpe (1964), Lintner (1965) and Black (1972) and has its origins in modern portfolio theory (Markowitz (1952, 1959)). This pricing model defines the expected return of an asset, $E(r)$, in terms of its relationship to the expected return of its market

$$E(r) = r_f + \beta\big(E(r_m) - r_f\big) \tag{2.1}$$

Here $E(r_m)$ is the expected return of the market, r_f is the risk free rate and β the exposure of the asset to the market risk.

There was a significant change in emphasis in the research following *Efficient Capital Markets*. The focus moved almost exclusively to equity markets, where a variety of anomalies to the efficient market hypothesis were identified. These include value (Basu (1977) and Rosenberg *et al.* (1985)), size (Banz (1981) and Keim (1983)), long-term reversal (De Bondt and Thaler (1985)) and cross-sectional momentum (Jegadeesh and Titman (1993)). There was particular focus on US markets, with others often limited to confirming results found there. Rouwenhorst (1998), for example, confirms cross-sectional momentum as a global phenomenon, following its identification in the US equity market (Jegadeesh and Titman (1993)).

The use of a single risk factor was also questioned, Black *et al.* (1972) provide an early challenge. Ross (1973, 1976) develops a theoretic framework, Arbitrage Pricing Theory, for multifactor asset pricing models, so that

$$E(r) = r_f + \sum_{f=1}^{F} \beta_f \,.\, E(RP_f) \tag{2.2}$$

Here β_f is the securities exposure to risk factor f, $E(RP_f)$ is the expected risk premium associated with factor f and F is the total number of risk factors. Tests for market efficiency are a joint test of the hypothesis and the pricing model used (Fama (1970) and Schwert (2003)). As a consequence, anomalous empirical evidence can be caused by or attributed to an incorrectly specified pricing model.

Fama and French (1996) make use of this framework to introduce value and size risk factors, developing a widely used three factor model

$$r = r_f + \beta_1(r_m - r_f) + \beta_2 SMB + \beta_3 HML \tag{2.3}$$

SMB and HML are the size and value factors respectively, following the notation in the original paper, and β_1, β_2 and β_3 are the asset's exposure to the risk factors. This new model successfully explained a number of previously identified anomalies. Efforts to improve the model for equity markets continue, Carhart (1997) proposes cross-sectional momentum as a fourth risk factor and Chen and Zhang (2010) propose an alternative three factor model, based on investment and return on assets. To date none of these has gained popularity and the three factor model remains central to the analysis of asset and investment returns.

The link between risk and return in the pricing model is captured by Malkiel (2003) in his practical definition of efficient markets as markets that '*do not allow investors to earn above average returns without accepting above average risks'* or, referring back to Equation 2.2, a portfolio with no exposure to risk factors (that is, all $\beta = 0$) has an expected return equal to the risk free rate. This has caused some problems in the study of alternative investments. While these generate returns in excess of the risk free rate (Capocci and Hübner (2004), Agarwal and Naik (2004) and Schneeweis *et al.* (2012)), traditional pricing factors only partially explain these returns (see, for example, Fung and Hsieh (2001) and Schneeweis *et al.* (2013)). In order to make the returns of alternative investments compatible with the efficient market hypothesis it became necessary to identify new risk premia. Fung and Hsieh (2001) introduce an option based factor to capture the risk in trend following, while more recently, Asness *et al.* (2013) and Koijen *et al.* (2013) have developed pricing factors for value, momentum and carry based on multi-asset class futures contracts.

The inter-temporal capital asset pricing model (ICAPM) provides an alternative approach to resolve the problem of the single risk factor in the CAPM. The theoretical frame work was developed by Merton (1973) and expands on earlier work by Black *et al.* (1972) which shows it is possible to construct a portfolio with no correlation to the market (a zero-beta portfolio) that has a return in excess of the risk free rate, an anomaly to the CAPM. The ICAPM is based on investors maximizing lifetime consumption given uncertain investment opportunity sets. The model can be expressed as

$$\alpha_i - r_f = \gamma_m(\alpha_M - r_f) + \gamma_i(\alpha_0 - r_f) \tag{2.4}$$

An investor is compensated for exposure to the market (γ_m) and investment opportunities (γ_i). The returns on the asset, market and zero-beta portfolio are α_i, α_M and α_0 respectively. It should be noted that γ represents a complex function of market and asset characteristics rather than a constant as in the case of APT models. Applied over a single period, there is no uncertainty in the investment state variable ($\gamma_i = 0$) and the model simplifies to the CAPM.

Fama (1996) reinterprets the model in a mean-variance efficient framework, based on investors hedging different aspects of future consumption-investment trade-offs through portfolios mimicking consumption risk, expressing the ICAPM as:

$$E(r) - r_f = \beta_m(E(r_M) - r_f) + \sum_{n=1}^{S} \beta_s(E(r) - r_f) \tag{2.5}$$

This derivation produce a model in a form equivalent to the multi-factor APT models. However, there is a limit to the extent that ICAPM and APT models can be regarded as different implementations of the same underlying model. While In and Kim (2007) show that the Fama-French value and size factors can provide good proxies for changing investment opportunities in the long run, Maio and Santa-Clara (2012) show that most of the common APT risk factors produce inconsistent (or impossible) results when used in the ICAPM framework.

Before leaving the discussion on efficient markets, it is worth highlighting three of the most common counter arguments to evidence of anomalies to the theory; incorrectly specified risk models, transaction costs and data mining.

In a sweeping dismissal of the theories of behavioural finance (these are discussed in detail in Section 2.5) Malkiel (2003) associates anomalies to incorrectly specified risk factors. In specific examples, the Fama and French (1996) definition of value and size as a risk factor removes a number of anomalies, while Carhart (1997) eliminates the problematic momentum effect by adding it to the standard Fama and French (1996) three factor model.

Fama (1991) allows for market frictions, such as transaction and information costs, in a practical interpretation of the efficient market hypothesis where '*prices reflect information to the point where marginal benefits of acting on information do not exceed the marginal costs*'. This allows statistically significant predictive relationships to exist in price returns without violating the efficient market hypothesis. Correct interpretation of such results can only be achieved by the inclusion of appropriate market friction costs in the analysis.

Data mining, that is finding random features in data that appear statistically significant but disappear when tested out of sample, can cause false identification of anomalies. Fama (1998) dismisses much of the anomalies to the efficient market hypothesis as "*chance results*" which "*tend to disappear with reasonable changes in technique*". Tomek and Querin (1984) show that it is possible to observe systematic components in random data and consequently that *ex-post* profitable trading rules can be found in such data. Schwert (2003) shows a number of anomalies disappear when tested out of sample, while specific to this study, Ready (2002) argues that positive evidence for a moving average based strategy can be attributed to data mining. A subtle variation, fine-tuning (over-fitting) parameters of a trading rule, provides a level of return that is not repeatable when applied outside the sample universe (see, for example, Boguth *et al.* (2011)) and suggest gross returns are above rather than below transaction costs.

2.2 The Performance of Time Series Momentum

The section reports the results of a survey of the literature for evidence on the presence of time series momentum. As the literature that deals explicitly with time series momentum does not appear until recently, Moskowitz *et al.* (2012) claim to have named the effect as recently as 2012, the survey cannot be limited by this definition. Instead it covers evidence for effects consequent to the phenomenon. In particular this includes evidence for continuation (autocorrelation) in price returns and the performance of trading strategies which rely on such continuations.

Where evidence is presented on trading performance, the focus is on returns in excess of the risk free rate, equivalent to a positive Sharpe ratio. The discussion also tracks the development of the methodologies used to capture and study time series momentum. It follows Park and Irwin (2007) in splitting the literature around a break occurring with the publication of Lukac *et al.* (1988b), which introduced significant improvements in methodology, including improved statistical analysis and incorporation of trading frictions. The analysis techniques move closer to practitioners', testing industry standard trading rules and basing conclusions on the performance of portfolios created from those rules.

Moskowitz *et al.* (2012), a key paper in the development of the theory of time series momentum, is discussed in detail. This section concludes by looking at a number of papers that present analyses of time series momentum over long time horizons.

2.2.1 Random Walks and Filters

The earliest evidence regarding return continuations focused on tests of the random walk model. Typical of these early papers was small sample size, with conclusions based on as little as a single index or a pair of futures. Analysis was based on higher frequency data, typically daily or weekly returns, and relationships tested over shorter time horizons than later work. A summary of the key early contributions is presented in Table 2.2.

The earliest investigations examined statistical properties of price series, particularly return autocorrelation, for compatibility with the random walk model. Kendall and Hill (1953) show that first order price changes were uncorrelated, while Osborne (1959) shows price changes of equities on the New York Stock Exchange were log normally distributed and the variance was directly related to the period of measurement. Alexander (1961) focuses on runs, consecutive price moves in the same direction, and finds their distribution consistent with a random walk.

Alexander (1961) attempted to resolve the conflict between the widespread use of technical analysis by practitioners and his finding that prices followed a random walk by developing and testing trading rules based on filters. Starting with the assumption that market noise obscures price patterns, simple filter rules were developed to exclude small price movements. These were shown to form the basis of profitable trading. As defined by Alexander (1961), the rules require that after a market rises (falls) x%, investors go long (short) and hold the position until the market falls (rises) x%.

Table 2.2
Price Return Continuations

The table summarises the key academic papers investigating price returns for evidence of continuation.

Paper	Focus	Markets	Conclusions
Kendall and Hill (1953)	Random walk	Equity sector indices, spot cotton and wheat	All series fit random walk model except cotton
Osborne (1959)	Random walk	Equities, NYSE	Distribution of price changes is consistent with random walk
Alexander (1961)	Filters	DJIA	No evidence against random walk but filters can produce excess returns
Houthakker (1961)	Stop orders	Wheat and corn futures	Stop orders improve returns over a buy and hold strategy
Smidt (1965)	Filters	Soybean futures	Some evidence of serial correlation.
Fama and Blume (1966)	Filters	Thirty US equities	Prices follow a random walk and filters are not profitable after costs
Stevenson and Bear (1970)	Filters	Corn and soybean futures	Trends are present in commodity prices
Taylor (1982)	Random walk	Ten commodity futures and GBP	Rejects the random walk hypothesis
Irwin and Uhrig (1984)	Technical trading rules	Eight commodities	Trading rules are generally positive, reject random walk.
Sweeney (1986)	Filters	Ten currencies against USD	Significant inefficiencies in currency markets

In the same year, Houthakker (1961) showed trading rules based on stop-loss orders were profitable while Smidt (1965) tests similar rules on soybean futures, concluding that there is some evidence of serial correlation in this market. As with Alexander (1961), Fama and Blume (1966) find no evidence of serial correlation in stock markets and that filter rules can generate positive returns. However, they conclude these profits are not robust to transaction costs. This foreshadows the later interpretation of an efficient market, which allows for price predictability provided it is not economically significant (Fama (1991)).

Stevenson and Bear (1970) find significant variation from efficiency in corn and soya bean futures over a twelve year period. They demonstrate evidence of reversals at a two-day horizon, serial correlation at a five-day horizon and positive returns for a range of filter based trading rules. Taylor (1982) finds evidence for serial correlation across nine commodities based on significant statistical improvements. Irwin and Uhrig (1984) test a set of six trend based technical rules, using a wide range of parameters and find that 87.5% are profitable. Taking a more negative view, Tomek and Querin (1984) show that it is possible to develop profitable trading rules *ex-post* on prices following a random walk. In the first extensive study of filters in currency markets after the breakdown of the Bretton-Woods system, Sweeney (1986) concludes that the presence of significant profits to a filter rule is evidence for inefficiency in the market.

Cutler *et al.* (1991) extend the range of markets which provide evidence for time series momentum by demonstrating autocorrelation of price returns in the US housing market and a variety of collectables, including coins, stamps and old master paintings.

2.2.2 Technical Trading Rules

The managed funds industry changed dramatically in the years after 1980. Assets under management in public futures funds grew one hundred fold from 1978 to 1984 (Irwin and Brorsen (1985)), while at the same time managers embraced computer technology and technical trading rules, with 80% of managed future funds relying on computer based technical trading strategies (Lukac *et al.* (1988a)).

This widespread use of technical trading strategies provided motivation for tests of their effectiveness, and explicitly or implicitly, the efficient markets hypothesis. A wide variety of different strategies were used in practice, Murphy (1999) provides an extensive, if uncritical, review of trading rules from an industry perspective. The majority are based on continuation patterns and Lukac *et al.* (1988b) highlights the similarity of these systems.

The publication of Lukac *et al.* (1988b) marks a significant change in the nature of the analysis (Park and Irwin (2007)). The sample set becomes broader, monthly data dominated and time horizons became longer. In addition, studies began to focus on the returns of portfolios formed from trading rules rather than individual instruments as the basis for conclusions. Research began to focus on trading rules used in the industry and the filters developed by Alexander (1961) tend to disappear from the literature.

Indicators based on time series momentum can be broken into two main categories, moving average and channel breakout (see Szakmary *et al.* (2010) for an example of this categorisation). Marshall *et al.* (2016) demonstrate the high correlation between the return series of portfolios generated from moving average and time series momentum rules. The moving average systems rely on comparing two moving averages a long and short formation period:

$$MA_{long} = \frac{\sum_{i=1}^{n_l} p_{t-i}}{n_l}, MA_{short} = \frac{\sum_{i=1}^{n_s} p_{t-i}}{n_s}, n_l > n_s \qquad (2.6)$$

The number of time periods in the long and short formation periods are n_l and n_s respectively. Positions are taken according to simple criteria, buy (go long) when $MA_{short} > MA_{long}$ and sell (go short) when $MA_{short} < MA_{long}$. The channel breakout indicator is based on a price moving outside a channel, itself defined as a function of past price history. Typically the top of the channel is defined by a trailing high and the bottom of the channel is defined by a trailing low.

$$CH_{top} = MAX(p_{t-1}, \dots, p_{t-n}), CH_{bottom} = MAX(p_{t-1}, \dots, p_{t-n}), \qquad (2.7)$$

Assets are bought (long) when the price moves above CH_{top} and sold (shorted) when the price crosses below CH_{bottom}.

The basic models allow significant variation, (see Murphy (1999)) including using multiple moving averages, alternative methods of averaging, a range of functions to define channels and different look-back periods for opening and closing positions. The ability of investigators to vary the parameters, allows critics, not unjustifiably, to cite data mining as the cause of successful tests, see Ready (2002) for an example of this line of argument.

Results across all markets and on all dates, tend to show that technical trend indicators produce positive excess returns. Lukac *et al.* (1988b) test twelve trading rules on twelve US futures contracts, including currency and interest rate futures, and find the majority generate positive returns. Mulvey *et al.* (2004) show that a portfolio of diverse futures contracts created using a moving average rule consistently generates excess return over a number of sub-periods and, significantly, that this excess return is not explained by the CAPM model.

Faber (2007) tests a moving average rule on five market indices and government bonds and find it outperforms a buy and hold strategy. Szakmary *et al.* (2010) test both moving average and channel rules on twenty-eight commodity futures over a period of forty-eight years. Individually, twenty-two and twenty-six of the futures had positive returns for the rules respectively. Both rules produce portfolios with statistically significant excess returns over both the full period and in each of four sub-periods.

Harris and Yilmaz (2009) is one of a few papers that increases the complexity of methodology used to capture time series momentum. In an echo of Alexander (1961), they build filters to extract the low frequency component of price movements of a group of nine currencies against the US dollar. They show that both the more complex rules and simpler moving average based rules generate excess returns. Allen and Karjalainen (1999) use a genetic algorithm to eliminate the effect of data-mining but find they cannot generate excess returns out of sample.

A significant number of studies focus on the currency market, showing positive excess return for both channel (Taylor (1994)) and moving average (Okunev and White (2003)) rules when applied to a basket of currencies. James (2003b) examines the performance of moving average rules and finds positive returns for thirteen out of fourteen currency pairs and a combined portfolio with a Sharpe ratio in excess of one. The author subsequently shows (James (2003a)) that the findings are robust to the parameters chosen, using formation periods of one to five months. Menkhoff *et al.* (2012b) investigate the performance of moving average rules over a thirty-five year period and show Sharpe ratios between 0.77 and 0.88 at the portfolio level.

The evidence is not unanimous. Ready (2002) suggests the success of moving average rules depends on data mining, although this conclusion is based on studies of a single index. Pukthuanthong-Le *et al.* (2007) analyse the performance of a moving average rule on a basket of six major currencies and show that while the strategy made substantial profits from 1975 to 1995, returns in the following ten years were negative but not statistically different from zero. This is consistent with the efficient market view that, once an anomaly has been identified, it will be arbitraged away (Fama (1970)).

Cross-sectional momentum is a trading strategy distinct from but correlated to time series momentum. Both rely on continuation of price returns, absolute in the case of time series momentum and relative for cross-sectional momentum. Moskowitz *et al.* (2012) highlight the similarities between the two measures and, in particular, show that time series momentum fully explains the return of cross-sectional momentum. As a consequence, evidence of excess returns for cross-sectional momentum can be interpreted as indirect evidence of time series momentum returns.

In the commodity markets both Erb and Harvey (2006) and Miffre and Rallis (2007) show that the strategy produces excess returns. These results are shown to be robust to a range of market based risk factors (Erb and Harvey (2006)), formation period and time period (Miffre and Rallis (2007)).

Both Burnside *et al.* (2011) and Menkhoff *et al.* (2012b) highlight positive excess returns to momentum in currency markets. Bhojraj and Swaminathan (2006) show a momentum portfolio formed from thirty-eight national equity indices over a thirty year period produce statistically significant returns. Stevenson (2009) shows a positive return to a cross-sectional momentum trading strategy based on eleven international real estate indices.

More generally, Asness *et al.* (2013) show momentum producing positive Sharpe ratios for four asset classes. Fuertes *et al.* (2010) combine momentum with carry to provide a profitable trading strategy.

2.2.3 Time Series Momentum

Moskowitz *et al.* (2012) is a key paper in the development of the understanding of time series momentum. The paper develops a rigorous definition of time series momentum, which extends beyond trading rules. The methodology developed has been used as a standard definition of time series momentum, including Baltas and Kosowski (2013) and Marshall *et al.* (2016). Hong and Satchell (2015) recognise moving average as a means of capturing the return to time series momentum as defined by Moskowitz *et al.* (2012). The time series return signal, TSM_t, is defined as the sign of the return, r, of an asset over a given time horizon, h, so

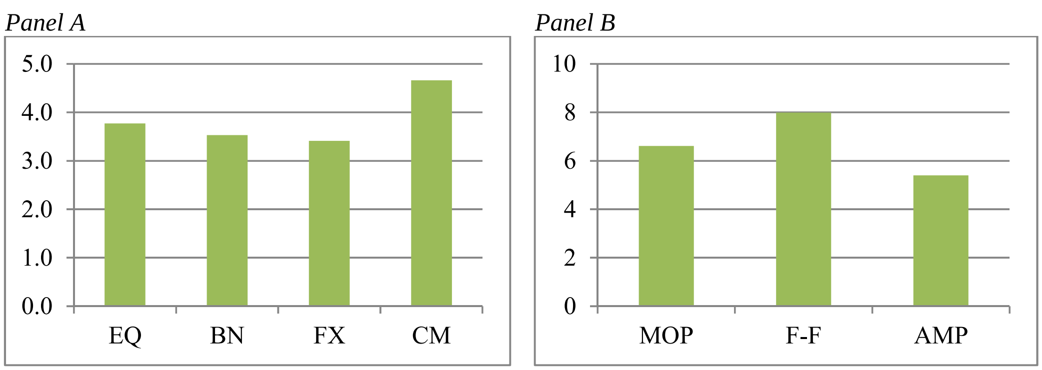
$$TSM_t = sign(r_{t,t-h}) \tag{2.8}$$

The paper extensively investigates the performance of a global portfolio and four asset class portfolios. Tests were carried out across a wide range of formation and holding periods. All formation periods up to two years, globally and for each asset class produce statistically significant excess returns. Performance was measured against three risk models; the Fama and French (1992) three factor model, the value and momentum (cross-sectional) factors developed by Asness *et al.* (2013) and a model specific to the paper. Focusing on the twelve month formation period, the key results, reproduced in Figure 2.3, shows statistically significant excess return across the four asset classes (Panel A) and the failure of risk factors to explain the returns of a global portfolio (Panel B).

A twelve month time series momentum trading rule was applied to each of the fifty-eight instruments in the data universe individually and excess returns were generated for all instruments.

Figure 2.1
The Excess Return of Time Series Momentum: 1985-2012

The figure show the test statistics of the excess return (intercept) of simulated time series momentum portfolios reported by Moskowitz *et al.* (2012). Panel A reports the performance of four asset class portfolios; equity indices (EQ), government bonds (BN), currencies (FX) and commodities (CM). Panel B shows the test statistics of the excess return of a diversified portfolio over three different risk models; a model specified in the paper (MOP), the Fama-French model (F-F), and the risk model (AMP) developed in Asness *et al.* (2013).



Source: Moskowitz *et al.* (2012)

The introduction of a standard definition of time series momentum compliments other recent formalisations of alternative risk factors based on trading strategies; carry (Koijen *et al.* (2013)) value and momentum (Asness *et al.* (2013)) and facilitates study of the phenomenon.

The paper identifies the presence of serial autocorrelation of returns in futures markets at horizons of up to twelve months. This finding opens up new possibilities for understanding time series momentum as well as justifying the use of twelve months as the standard formation period[3]. In addition, time series momentum is demonstrated across all major asset classes, both in terms of excess returns and the presence of

[3] Cutler *et al.* (1991) provide evidence of autocorrelation in an earlier period, 1960 to 1988, but not in the context of times series momentum.

autocorrelations in price returns. This indicates the mechanism of time series momentum is universal and that investigation of the effect should focus on global rather than market or asset specific explanations.

Finally, the paper highlights the correlation between time series momentum and cross-sectional momentum, showing that the returns to cross-sectional momentum are fully captured by its exposure to time series momentum.

2.2.4 Long Term Performance

A number of studies examine the performance of trend following over the long term. The early studies are typically based on a US stock index. Neftci (1991) shows that a moving average indicator has predictive power for the Dow Jones Industrials over two centuries up to 1976. Brock *et al.* (1992) identify statistically significant returns to both moving average and channel rules from 1896 to 1987, with statistically significant results in each of four sub-periods. Siegel and Coxe (2002) provide evidence that a moving average rule improves timing on the stock market over the period 1885 to 1997. Faber (2007) confirms the long term excess return over the period from 1900 to 2005. In addition, he shows that the trading rules work out of sample in four additional markets (UK, France, Germany and Australia) and are robust to the choice of formation period, generating similar results while varying this from six to fourteen months.

Two later papers test the idea that the findings of Brock *et al.* (1992) can be attributed to data mining with contrasting results. Sullivan *et al.* (1999) use a bootstrap methodology and conclude the results are robust while Ready (2002) uses a genetic algorithm to argue they are the result of data mining.

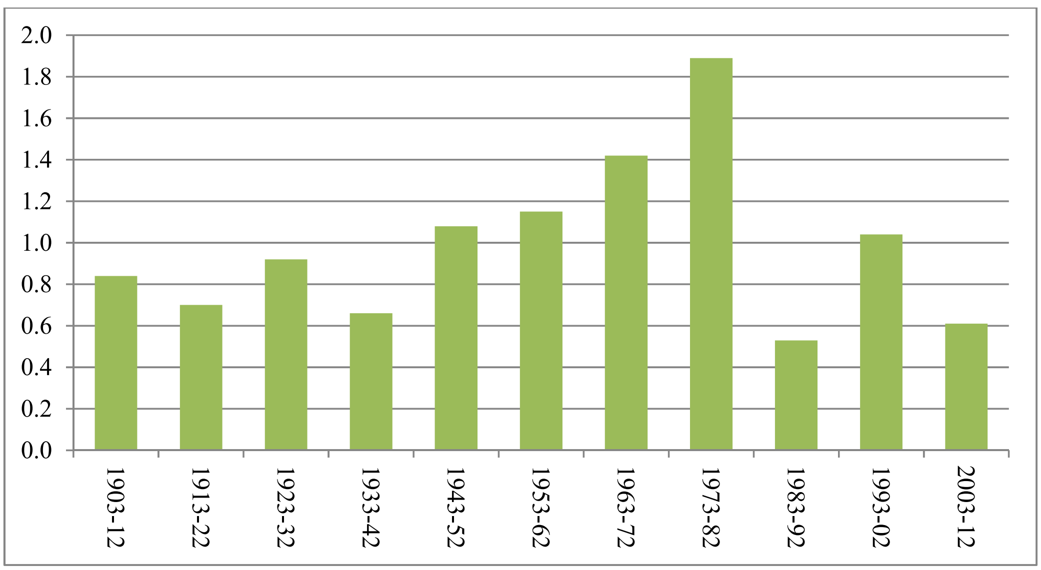
Two recent studies have attempted to extend the return series of momentum backwards in time by analysing the performance of a multi asset class portfolio. Hurst *et al.* (2012) follow an approach similar to Moskowitz *et al.* (2012) and base their analyses on the performance of simulated portfolios created using a time series momentum strategy. The portfolio comprises of instruments with exchange traded futures prices, supplemented with synthetic prices to extend the sample period backwards. The returns of the portfolio are broken down into ten year periods, reproduced in Figure 2.4. A positive Sharpe ratio is reported for each decade, the lowest value being 0.53. These results are net of transaction costs and the standard fee structure of 2% (management fee) and 20%

(incentive fee). The returns after 1983, which are primarily based on exchange traded futures data, remain high.

Lempérière *et al.* (2014) move the time series back a further century, showing positive and statistically significant Sharpe ratios for each fifty year period from 1800. The results for the earlier periods should be treated with caution as they are based on spot prices rather than future prices. However, results from 1960, based on exchange traded contracts and arranged in decades, confirms the result of Hurst *et al.* (2012).

Figure 2.2
Simulated Performance of Time Series Momentum: 1903-2012

The figure shows the Sharpe ratio of a simulated portfolio of futures generated using a time series of momentum strategy reported by Hurst *et al.* (2012). The portfolio is constructed of futures based on equity indices, government bonds, currencies and commodities. The Sharpe ratio is calculated on the portfolio return net of trading costs, management fee (2%) and performance fee (20%).



Source:Hurst *et al.* (2012)

2.3 Commodity Trading Advisors

Times series momentum is generally believed to be the dominant factor of CTAs (see Elton *et al.* (1987) and Lukac *et al.* (1988a) for early examples). The assumption is tested more rigorously by Fung and Hsieh (2001), who show trend following factors explain a significant portion of CTA returns while Baltas and Kosowski (2013) demonstrate the high correlation between CTA and trend following returns.

This provides an alternative approach to assessing the performance of time series momentum as CTA returns data provides an indirect measure of the returns to time series momentum. Realized returns have two important characteristics, they are net of transaction costs and out of sample. Evidence of positive returns derived from CTA performance cannot be dismissed as the results of either under incorporation of transaction costs or data mining, two of the common objections to results anomalous to the efficient market hypothesis.

Fund databases are subject to significant biases which, if not correctly accounted for, can lead to significant over statement of performance (Brown *et al.* (1992)). Fung and Hsieh (1997, 2000) provide an analysis specific to the CTA industry, highlighting the potential problems caused by survivorship bias, back-fill bias (instant history in their terms) and selection bias. Fung and Hsieh (2009) highlight issues that can arise from the dynamic structure of databases, Aggarwal and Jorion (2010) focus on one aspect of this, the significant survivorship bias the can result from merging databases. A number of recent papers including Bhardwaj *et al.* (2014), Jorion and Schwarz (2014) and Getmansky *et al.* (2015), develop methods to eliminate these biases. Bhardwaj *et al.* (2014) further show the Sharpe ratio of the aggregate performance of funds in the TASS CTA database drops from 0.77 to 0.18 after accounting for biases.

CTAs do not all operate trend following strategies, operate in limited asset classes or operate mixed strategies. While self-classification can help identify trend followers it provides latitude for funds operating in the same classification to conduct divergent behaviour. Evidence from the mutual fund industry finds that funds within the same self-classified segment can have quite different return generating processes (Brown and Goetzmann (1997)).

The performance of CTAs is reported net of (often substantial) management fees and the return to underlying strategies is significantly higher than that delivered to CTAs investors and recorded in the databases. Bhardwaj *et al.* (2014) estimate that CTAs received an annual fee equivalent to 4.3% of assets under management per annum between 1994 and 2012, while French (2008) provides a similar value for hedge funds in general.

The performance records of CTAs can be traced back to about 1980, Irwin and Brorsen (1985) note that there was only one publicly traded CTA in 1978, and the earliest analyses of their performance appears at the end of the decade. Many studies neglect the early evidence due to data bias problems (see, for example, Kazemi and Li (2009) and

Bhardwaj *et al.* (2014)), with 1994 being a common start date for analysis. A very early study, Elton *et al.* (1987) estimates negative performance, showing CTAs underperform both stocks and bonds. This is one of very few papers reporting a negative Sharpe ratio for average performance of CTAs. The same authors later (Elton *et al.* (1990)) reassess their findings on a broader dataset, confirming the original finding of underperformance against stock and bond indices, but reporting a positive Sharpe ratio for average performance. In contrast, Schneeweis *et al.* (1991) examine the performance of CTAs from 1980 to 1988 and estimates a higher return than either equity or bond indices. Irwin *et al.* (1993) study performance over a similar period (1979 to 1989) and find that while CTAs generate positive performance on average, their Sharpe ratio is only marginally positive. However, the average fee charged in this period was estimated to be in the range of 18% to 20% of assets under management per annum (Irwin *et al.* (1993)). It should be noted that all these papers predate the important work by Fung and Hsieh (1997, 2000) on the biases inherent in CTA databases.

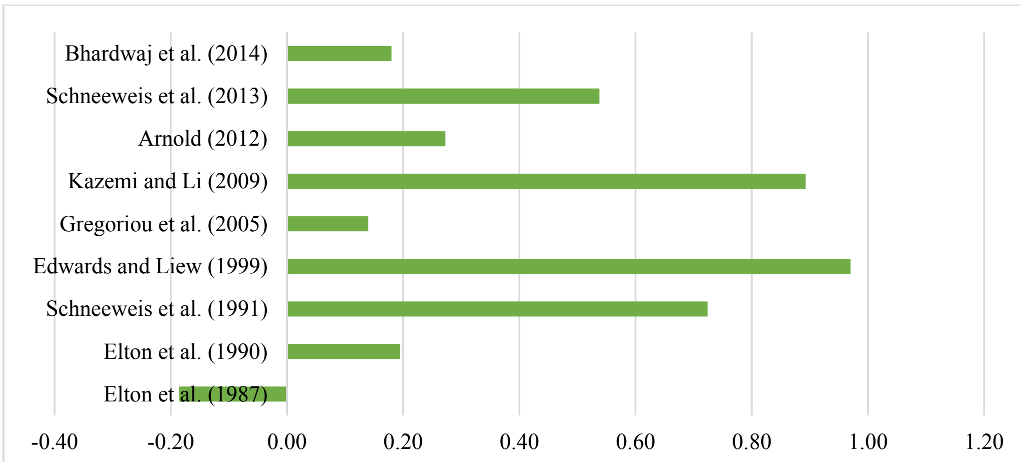
Edwards (1998) finds an equal weighted CTA index has an average return of 23.2% (Sharpe Ratio 0.98) from 1982 to 1996. Gregoriou *et al.* (2005) shows that all categories in the BarclayHedge CTA database have positive Sharpe ratios and statistically significant excess returns over a variety of standard risk models, although the models explain less than 2% of price movement. Kazemi and Li (2009) examine the CISDM database from 1994 to 2004 and conform the excess returns of the aggregate performance. Arnold (2012) provides a long run analysis of CTA performance, from 1993 to 2010, again providing strong evidence of an aggregate return above the risk free rate. Schneeweis *et al.* (2013) examine the performance of CTAs based on a variety of indices and report positive performance.

Bhardwaj *et al.* (2014) argues for a more negative view of the value of CTAs as investment vehicles. After allowing for biases, they estimate the CTAs in the Lipper-TASS database returned a statistically insignificant 1.8% above the risk free rate per annum between 1994 and 2012. However, when fees are added back in, the gross return is significantly above the risk free rate.

Taken as a whole, the evidence, summarized in Figure 2.3, supports the contention that that CTAs on aggregate and, by implication, time series momentum trading strategies, generate a return in excess of the risk free rate.

Figure 2.3
The Performance of Commodity Trading Advisors

The figures shows the Sharpe ratios of aggregate CTA performance derived from the literature. Where the Sharpe ratio is not presented directly, it is derived from the available data in the paper, using the average yield of three month US treasury bills as the risk free rate. When multiple values are reported, preference is given to the value associated with equal weighting and/or systematic CTAs.



2.4 Theories of Time Series Momentum

The preponderance of evidence presented in the previous two sections indicates time series momentum strategies produce returns in excess of the risk free rate. This section examines the literature for explanations of these returns.

2.4.1 Traditional Pricing Factors

The standard approach to explaining a return in excess of the risk free rate within the efficient markets paradigm is to associate it with exposure to risk factor(s), using arbitrage pricing theory (see, for example, Fung and Hsieh (2002) and Kat and Miffre (2008)). This can be expressed as

$$r_t - r_{f,t} = \alpha + \sum_{f=1}^{F} \beta_f \,.\, (f_{f,t} - r_{f,t}) \tag{2.7}$$

where r_t is the return at time, t, $r_{f,t}$ is the risk free rate at time t, $f_{f,t}$ is the return of risk factor f at time t, β_f is the exposure to risk factor f and α is the excess return. Under the efficient market hypothesis $\alpha = 0$ and this equation becomes equivalent to Equation 2.2.

The interpretation of a statistically significant α is subjective, interpreted by different authors as a risk premium (Asness *et al.* (2013)), evidence of missing pricing factors (Malkiel (2003)) or a challenge to the efficient market hypothesis (Moskowitz *et al.* (2012)). This discussion does not make a distinction but, for the purposes of this section, regards evidence of an excess return from a mechanically derived portfolio as a potential risk factor.

Factors which have been used to analyse the return of long only investments, typically stock and bond portfolios, are referred to here as traditional risk factors. It is convenient to split these factors into asset class factors and style factors along the lines of Sharpe (1992). Asset class factors consist of long positions in a basket of assets representing a market or subsection of a market. Style factors are more nebulous but can be considered to represent the spread between the return of two asset class factors. Sharpe (1992) identifies twelve asset class factors for analysing the performance of mutual funds, repeated in Table 2.3. Most analyses use a subset of these.

Table 2.3
Asset Class Factors

The table lists the asset classes suggested in Sharpe (1992) to understand the returns of equity and bond mutual funds in the United States.

Debt	**Equity**
Treasury Bills	Large Capitalization Value US Equities
Intermediate Term US Government Bonds	Large Capitalization Growth US Equities
Long Term US Government Bonds	Medium Capitalization US Equities
Corporate Bonds	Small Capitalization US Equities
Mortgage Back Securities	European Equities
Non-US Government Debt	Japanese Equities

Edwards and Liew (1999) find no correlation between the return of CTAs and five asset classes. Fung and Hsieh (2001) show eight different sets of asset factors fail to explain the return of trend-following funds. The same authors later use a three asset model (small capitalization equities, high yield bonds and emerging markets) to explain the returns of sixteen hedge fund classes (Fung and Hsieh (2002)). They show that while the model can explain a portion of the returns of most classes, the majority still have statistically significant excess returns. In addition, the three factors fail to explain the return of managed futures, reporting the lowest coefficient of determination for that class.

Hasanhodzic and Lo (2006) and Amenc *et al.* (2010) highlight the difficulty in replicating alternative investment returns through factor exposures in linear and non-linear frameworks respectively. Schneeweis *et al.* (2012) show that traditional factors have some power to explain the returns of hedge funds in general, they do not (Schneeweis *et al.* (2013)) explain the return of managed futures.

The second set of factors used are based on investment style. These are size and value spreads for equity markets (Fama and French (1992)) and term and credit spreads for bond markets (Fama and French (1993))[4]. More recently, equity momentum, originally proposed as a risk factor by Carhart (1997), has been used as such by Fama and French (2012). When applied to alternative investments, style factors have some success in explaining a portion of the returns of some categories but fail to capture any of the risk of CTAs. Liang (2003) shows that while value and size help explain the return of hedge fund indices, they have little explanatory power for CTA returns. Burnside *et al.* (2006) similarly show little explanatory power in traditional factors for the returns to currency strategies. Schneeweis *et al.* (2013) confirm the findings of Liang (2003) while also including the equity momentum factor in their analyses.

2.4.2 Alternative Risk Premia

The limited success of traditional factors in explaining alternative investment returns has led to the development of factors specifically for alternative strategies. These factors are derived from the returns of portfolios generated from simple mechanical trading rules. These methods are generally analogous to the methods used to create traditional factors but applied to the universe of instruments traded by alternative managers.

Fung and Hsieh (2001) developed an early set of risk factors specifically to capture the risk associated with trend-following strategies, defining five risk factors, each based on a specific asset class (the four standard classes and short term interest rates). In each case the return series was defined as the return of a portfolio of a look-back straddles for a basket of assets. This model has had success in explaining the returns of individual trend following CTAs, generating an average adjusted r-squared of around 20%. Fung and Hsieh (2004) combine three of their option factors with four traditional measures to develop a seven factor model for bench marking hedge fund performance. This model

[4] The credit factors have an earlier interpretation as economic factors and will be discussed in this context below.

continues to be extensively used, see Avramov *et al.* (2011), Schneeweis *et al.* (2012) and Baltas and Kosowski (2013) for recent examples.

While these factors have successfully explained a portion of the return of CTAs, there has been some recent criticism of their use as performance benchmarks. Bhardwaj *et al.* (2014) highlight the negative premium associated with the factors, which may result in over-estimation of excess return or manager skill.

Carry, also known as basis or roll, is the expected return of a future contract if the underlying spot price does not change (Koijen *et al.* (2013)). For financial assets (equities indices, bonds and currencies) this measure can be calculated mechanically as a function of income and funding cost. It can only be measured from traded data for commodities where the futures price is a complex function of various factors including inventory, cost of storage and supply risks. The literature on carry focuses on foreign currency and commodity markets.

In the currency markets, a carry strategy is implemented by buying high yielding and selling low yielding currencies. Bilson (1980) and Hansen and Hodrick (1980) provide early evidence of positive returns for the strategy. More recently, Burnside *et al.* (2011) and Menkhoff *et al.* (2012a) provide evidence of a risk premium associated with the carry trade.

Erb and Harvey (2006) and Gorton and Rouwenhorst (2006) both show that carry explains a significant proportion of the total return of commodities. In addition, Erb and Harvey (2006) find a long-short portfolio of commodities, based on a carry rule, produces a significant excess return. More recently, Gorton *et al.* (2013) show a linear relationship between carry and future return while Erb and Harvey (2016) confirm their earlier finding of the importance of carry to commodity returns.

In equity markets, dividend yield is the equivalent of carry. It has long been known that dividend yield has some predictive power, see Ball (1978), Basu (1983) and Fama and French (1988) for early evidence. More recently, Dangl and Halling (2012) confirm this, presenting evidence of time varying predictability.

Koijen *et al.* (2013) unify the research on carry, measuring it in four asset classes. They provide a standard definition and present evidence documenting the prevalence of carry as an alternative risk premia across all four classes.

Duarte *et al.* (2007) provide an early example of using carry as a risk factor. More recently it has been used to analyse the returns of cross-sectional momentum strategies in currency markets (Burnside *et al.* (2011)) and the performance of CTAs (Bhardwaj *et al.* (2014)). Moskowitz *et al.* (2012) suggest that carry is a significant cause of the time series correlation found in futures markets.

The use of value and momentum as risk factors can be traced back to the literature on equity momentum where they play a significant role in the development of asset pricing models, see Fama and French (2012) for a recent overview in international equity markets.

Cross-sectional momentum, discussed above as supporting evidence for time series momentum, has been shown to produce excess return (or risk premia) for portfolios of commodities (Miffre and Rallis (2007)), currencies (Burnside *et al.* (2006)) and international equity indices (Bhojraj and Swaminathan (2006)).

Value has a long history as both an investment style (described in Graham and Dodd (1934)) and a risk factor (Fama and French (1996)) in equity markets, it has not had featured significantly outside this area, possibly a consequence of the difficulty in finding a consistent measure across asset classes.

Asness *et al.* (2013) provide comprehensive definitions of both value and momentum factors for the four standard asset classes. Momentum is defined across all asset classes using past twelve months relative price movement, the standard measure from the equity literature (see, for example, Jegadeesh and Titman (1993) and Fama and French (1996)). Value, unlike other risk premia, has asset class specific definitions. The definition for equity indices is consistent with that used for individual equities, based on the aggregate book to price ratio. The value factors for bonds and commodities is defined in a similar fashion to long term reversal in equity markets (De Bondt and Thaler (1985)), while currency value is derived from changes in purchasing price parity.

Moskowitz *et al.* (2012) use value and momentum risk factors, as defined in Asness *et al.* (2013), to explain a third of the return of time series momentum, although the cross-sectional momentum factor is dominant. Bhardwaj *et al.* (2014) show that while momentum risk premia in commodities and currencies have significant explanatory power on the returns of CTAs, value and momentum factors based on equity indices have no significant impact.

Hedging pressure has a long history in investigations of the performance of commodities and offer a potential risk factor for this market. Keynes (1930) divides participants into speculators and hedgers, with hedgers paying a premium to speculators. He postulated that hedgers were dominated by producers so, under the theory of normal backwardation, the premium would flow to long holders. Bessembinder (1992) and De Roon *et al.* (2000) both demonstrate a link between hedging pressure and returns. Moskowitz *et al.* (2012) apply the disequilibrium directly to time series momentum, suggesting that speculators implementing trend-following strategies, receive a premium from hedgers for providing liquidity. Basu and Miffre (2013) create a hedging pressure factor based on a long short portfolio and show it has a significant positive expected return. This risk factor has not as yet been extended to other financial markets.

2.4.3 Macroeconomic Risk

2.4.3.1 Macroeconomic Variables

A number of papers investigate the link between investment returns and economic factors, in effect using economic variables as risk factors within the arbitrage pricing theory framework. The factors used in the key papers are shown in Table 2.4, highlighting a significant overlap.

An early work (Chen *et al.* (1986)) shows that a set of eight economic variables have significant explanatory powers on returns of a US equity index. Fama and French (1989) use a subset of these to explain the return of the bond market. Less directly, Chen (1991) uses economic variables to predict economic growth and consequently the return of the stock market.

A number of papers test the use of economic risk factors to explain the returns to cross-sectional momentum. While it is generally agreed linear models do not provide good explanatory power (see, for example, Griffin *et al.* (2003)), other conclusions differ. Chordia and Shivakumar (2002) argue that the majority of cross-sectional momentum profitability comes from the portion of equity returns explained by macroeconomic factors and has a time varying expected return. In contrast, Griffin *et al.* (2003) fail to find any evidence of macroeconomic factors explaining momentum across sixteen countries, repeating the conditional tests of Chordia and Shivakumar (2002).

Table 2.4
Economic Variables and Investment Returns

The table lists the economic variables cited by papers investigating the relationship between the macroeconomy investment returns. The exact details of factor definitions can vary between papers.

	Term Spread	Default Spread	Dividend Yield	Expected Inflation	Unexpected Inflation	Short Term Rate	Consumption	Industrial Production	Unemployment	Oil Price	Stock Market
Chen *et al.* (1986)	•	•		•	•	•	•	•		•	
Fama and French (1989)	•	•	•								
Chen (1991)	•	•	•			•		•			
Chordia and Shivakumar (2002)	•	•	•			•					
Bali *et al.* (2014)	•	•	•	•		•		•	•		•

2.4.3.2 Volatility and Uncertainty

An alternative approach links the performance of assets and trading strategies to the risk (volatility) in economic conditions rather than the conditions themselves, in effect economic risk is defined as a risk factor.

Both Melvin and Taylor (2009) and Menkhoff *et al.* (2012a) develop measures of currency volatility and use innovations in their measures to explain the returns to carry based trading strategies. Lustig *et al.* (2011) provides evidence of a link between currency market returns and equity market volatility.

Grobys *et al.* (2016) use currency return dispersion as a proxy for global economic risk and demonstrate a relationship between momentum pay-off and this risk factor. The option factors of Fung and Hsieh (2001) implicitly link time series momentum with market volatility. Daniel and Moskowitz (2014) show a relationship between momentum returns and market volatility for multiple asset classes. Higher moments have also been cited as risk factors, in particular crash risk. Brunnermeier *et al.* (2008) provides evidence crash risk is a priced risk in the returns of the carry trade.

Two recent papers provide methods to create measures of general economic risk. Kritzman and Yuanzhen (2010) develop a generic methodology to measure financial turbulence and use it to show turbulence effects the performance of portfolios of currencies, based on a carry rule. The same authors (Kritzman *et al.* (2012)) later show that market specific versions of their measure can explain return variations in a number of dynamic strategies.

Bali *et al.* (2014) build an index of macroeconomic risk (uncertainty) as a function of eight underlying economic variables. They demonstrate that the measure has a statistically significant relationship with the performance of hedge funds and that the sensitivity of hedge funds to economic uncertainty is important in explaining the cross-sectional dispersion of these returns.

2.5 Behavioural Finance

Behavioural finance is the most popular alternative market paradigm to efficiency. It posits the existence of non-rational participants in financial markets and that their irrational actions force market prices away from efficient levels. This is in contrast to the standard view which sees economic agents as rational, able to incorporate new information instantly and make consistent decisions. A consequence of efficient markets is that all prices are effectively fundamental prices (Barberis and Thaler (2003)).

This discussion does not attempt to provide a full overview of the field of study but rather to highlight behavioural mechanisms that could be used to explain time series momentum. The bulk of both theory and empirical work in behavioural finance focuses on equity markets, in particular those in the US.

The anomalies identified can be divided into two categories; irrational (sub-optimal) behaviour and price predictability. Evidence for irrational behaviour includes evidence that the volume of trading is higher than expected, equity volatility is greater than justified by changes in earnings (Shiller (1980)) and evidence that the equity risk premium is too high (Mehra and Prescott (1985)). The evidence for predictable prices, previously discussed in Section 2.1, includes cross-sectional momentum (Jegadeesh and Titman (1993)), long-term reversal (De Bondt and Thaler (1985)) and value (Basu (1977), but can be traced back to Graham and Dodd (1934)). Fama (1991) indicates that in total up to 40% of the variation in price returns can be explained at long horizons, although he indicates this is compatible with the efficient market hypothesis.

The discussion of behavioural finance below is uncritical but the topic remains controversial, with significantly less support in the literature than the efficient market hypothesis. The majority of the anomalies listed above have been explained within the framework of the efficient market hypothesis, at least to the satisfaction of its proponents. The explanations include mis-specified risk factors (Malkiel (2003)), improper incorporation of costs (Fama (1991)) or simply chance results (Fama (1998)).

Behavioural finance has its origin in the field of behavioural psychology. Simon (1955) argues that individuals, due to limited cognitive ability, are not able to make fully rational choices, required by both classical economics and the efficient market hypothesis. Instead they use heuristics to simplify the decision making process and reach satisfactory, rather than optimal, outcomes. As series of experiments in the following decades, Bem (1972) provides a summary, confirms that individuals do not act as fully rational agents. The cognitive errors fall into two general categories; those based on belief and those based on preference (Barberis and Thaler (2003)).

A series of papers by Kahnman and Tversky (Kahneman and Tversky (1972, 1973); Tversky and Kahneman (1973, 1974)) investigates errors based on belief. They focus on two heuristics, availability and representativeness. The presence of these biases in individuals' decision making processes is experimentally demonstrated and shown to lead to overconfidence in the accuracy of predictions, extrapolation (or over-emphasis) of recent data, reliance on available data and failure to incorporate both base rate (*a priore*) probability and sample size. Tversky and Kahneman (1974) conclude that when faced with uncertainty, errors in decision making are both '*systematic and predictable*'.

In addition to misinterpreting data, individuals also exhibit overconfidence in their own ability to make decisions. Overconfidence is increased by self-attribution bias, the tendency of individuals to attribute events that confirm their actions to skill, while negative events are put down to chance (Bem (1965)). Griffin and Tversky (1992) demonstrate that experts are more likely to display overconfidence. Odean (1998b) links overconfidence to a number of sub-optimal behaviours observed in equity markets, including over-trading.

A second set of biases make individuals slow to update their belief with new information. Confirmation bias is the tendency to prefer evidence that supports prior views (Gilovich *et al.* (2002)). Belief perseverance posits that individuals hold to their beliefs longer than is warranted by the evidence[5]. Lord *et al.* (1979) show that not only do individuals seek out information to support their views but interpret information in line with prior beliefs.

The second category of cognitive biases centres on preferences; where individuals exhibit sub-optimal or inconsistent preferences. Kahneman and Tversky (1979) introduce prospect theory, arguing that outcomes are judged from gains and losses, rather than final position and that individuals have asymmetric utility curves. Thaler and Johnson (1990) show that preferences are path dependent. More recently, Marchiori and Warglien (2008) show regret avoidance is a significant factor in decision making. Odean (1998a) uses this bias to explain the disposition effect, investors' preference for selling winners rather than losers.

Shefrin and Statman (2000) develop behavioural portfolio theory. They argue that individuals build portfolios based on factors which do not match the mean variance approach favoured by modern portfolio theory methods. They further show that, under this theory, the efficient frontier is different from the mean variance efficient frontier. In behavioural portfolio theory, investors do not have symmetric utility curves, but look at investments from a safety first perspective, not wanting to fall below a certain level of wealth.

The literature does not extensively deal with time series momentum, however there are behavioural explanations for price continuations in the analysis of cross-sectional momentum in equity markets. This section concludes with a discussion of this literature as it provide theories of price continuation (auto-correlation) potentially applicable to time series momentum.

The excess returns due to the strategy is demonstrated by Jegadeesh and Titman (1993) for US equities and later shown to be a global phenomenon by Rouwenhorst (1998). Fama (1998) recognizes it as a "*puzzle*" in need of further investigation. The

[5] It's worth noting Barberis and Thaler's (2003) example of belief perseverance, if only to highlight the distance between the two sides, that is "*if people start out believing the EMH, they may continue to believe it long after compelling evidence to the contrary has emerged.*"

investigations, key papers are listed in Table 2.5, produce a variety of explanations, both compatible with and contrary to the efficient market hypothesis.

Table 2.5
Explanations of Cross-sectional Momentum

The table lists selected explanations, both rational and behavioural, of cross-sectional momentum found in academic literature.

Paper	Cause	Mechanism
Carhart (1997)	Risk	Momentum is a risk factor and so compatible with the efficient market hypothesis
Barberis *et al.* (1998)	Conservatism	Investors underreact to news, leading to its gradual incorporation into market prices
Daniel *et al.* (1998)	Self-attribution	Asymmetric incorporation of public news on private information leads to positive feedback trading
Hong and Stein (1999)	Noise traders	The interaction between noise traders and news watchers creates under reaction to news.
Grinblatt and Han (2002)	Disposition effect	The unwillingness of investors to sell losing stocks causes under reaction to news.
Lesmond *et al.* (2004)	Trading costs	The costs of implementing the strategy are greater than the gross profits.

Carhart (1997) defines momentum as a risk factor, effectively extending the Fama and French (1996) three factor model to four factors. Conrad and Kaul (1998) argue for a risk based explanation, based on time variation of risk in cross-sectional return. Lesmond *et al.* (2004) argue that while the data suggests a profitable trading strategy, this disappears in the presence of trading costs, although Korajczyk and Sadka (2004) suggest that 5bn USD need to be invested in the strategy before the returns to momentum disappear.

Barberis *et al.* (1998) focus on conservatism and representativeness to model investor sentiment. Conservatism allows investors to under-react to a news item as they are slow to update prior beliefs, while representativeness means investors over react to a series of positive (or negative) news events. In both cases price continuation is predicted in the short term, while the overreaction model suggests longer term reversals.

Daniel *et al.* (1998) build a model of investors' overconfidence in private information and self-attribution bias, which shows these behavioural biases lead to short-lag auto correlation in the return of financial assets. Their work shows that the effects of overconfidence include negative long lag correlations (long term reversal) and public event return predictability, while biased self-attribution leads to short-lag autocorrelation (momentum). The evidence of a link between market declines, falls in confidence and poor returns to momentum (Cooper *et al.* (2004)) is compatible with this model.

Hong and Stein (1999) propose a model based on the interaction of heterogeneous market participants. Unlike other theories, it does not rely on a specific bias, but on bounded rationality. Interaction between news watchers and momentum traders results i under-reaction to news, resulting in momentum as the price of the asset moves towards its fundamental value. In a theoretical model, Goldstein *et al.* (2014) show that splitting a market between hedgers and speculators creates opportunities for excess returns through a similar mechanism.

Finally, Grinblatt and Han (2002) use the disposition effect (prospect theory) to develop a market model to explain cross-sectional momentum. The unwillingness of investors to close losing positions results in an under-reaction to news, which in turn causes a divergence between the market price and fundamental value of an equity. The elimination of this divergence leads to positive auto correlation in returns.

In a rare application of behavioural theories to futures markets, Hurst *et al.* (2013) develop a model to explain time series momentum. The model, which combines under-reaction followed by delayed over-reaction, reflects earlier work on cross-sectional momentum in equity markets (Daniel *et al.* (1998) and Hong and Stein (1999)). The model is derived from a decomposition of the market's response to information that changes the fundamental value of an asset.

Under the efficient market hypothesis, news should be fully incorporated into asset prices immediately; that is when the market become aware of news prices should move directly to new fundamental values. In the Hurst *et al.* (2013) model, shown in Figure 2.4, the market first under-reacts to news, moving slowly towards the fundamental value and the over-reacts, driving the price above the fundamental value. Together these two phases constitute the trend in an asset price with behavioural biases proposed as the source of both under and over-reaction.

In the third and final stage, the price reverts to its fundamental value as distortions due to behavioural biases diminish. This leads to the widely observed long term reversal (see, for example, Shen *et al.* (2007) and Moskowitz *et al.* (2012)). While this is not directly related to a discussion of time series momentum, it does allow a single behavioural model to explain two apparently unrelated market phenomena.

Behavioural finance is less parsimonious is explaining the causes of the under- and over reaction, providing multiple mechanisms to explain both. Asymmetric utility curves (Kahneman and Tversky (1979)) cause investors to close winning positions too soon (Odean (1998a)) slowing market responses. Both anchoring (Tversky and Kahneman (1974)) and belief perseverance (Lord *et al.* (1979)) result in investors being slow to update their valuations, referring to an arbitrary past value or prior belief respectively. Under confirmation bias (Gilovich *et al.* (2002)) investors underweight information contrary to prior beliefs, delaying changes to their position.

Figure 2.4
Stylised Model of a Price Trend

The figure shows the life cycle of a trend based on the model of Hurst *et al.* (2013). New information changes the fundamental value of an asset. The market first under-reacts to this, then over-reacts, before finally reverting to the new fundamental value.

Under-reaction results in a series of price movements in the same direction. Behavioural finance provides a variety of mechanisms that predict overreaction as a consequence of serially correlated price changes. These generally consist of behavioural effects that bias investors to trade in the direction of the trend. Availability (Tversky and Kahneman (1973)) and representativeness (Tversky and Kahneman (1974)) both lead investors to assume a recent price changes will continue. The effects are amplified by sample size neglect (Gilovich *et al.* (1985)) which leads investors to over-extrapolate recent price returns. Regret avoidance (Marchiori and Warglien (2008)) encourages investors to follow an established trend to avoid missing further profits. Finally, due to herding

(Welch (2000)) and feedback trading (Hong and Stein (1999)) investors tend to follow recent successful trades of other investors.

It should be noted that market mechanisms other than behavioural biases can cause or contribute to these effects. The presence of non-profit maximising market participants, typically central banks (see, for example, Saacke (2002) and Bhanot and Kadapakkam (2006)), can result in markets diverging from efficient behaviour. A number of studies show that market inefficiencies also slow reaction to new information (see, for example, Mitchell *et al.* (2007), Duffie (2010) and Buss and Dumas (2015)).

While developing the model, Hurst *et al.* (2013) do not specifically test for behavioural biases beyond demonstrating the presence of both time series momentum and reversals in markets. This highlights a key issue in the development of behavioural finance. Many phenomena, including both under-reaction and over-reaction, have multiple behavioural explanations. This makes it difficult, if not impossible, to empirically test for an individual bias. This problem and the consequent ambiguity in results is emphasised by Moskowitz *et al.* (2012) who highlight the fact that their empirical results in a study on time series momentum are compatible with a variety of both behavioural and rational market models. In consequence, while the behavioural biases cited here have been shown to exist in individuals to the satisfactions of behavioural psychologists, their effect on financial markets and consequent impact on asset prices, if any, has yet to be demonstrated to the satisfaction of many.

2.6 Current State

Before concluding, the current state of the literature relevant to time series momentum is summarised below.

A significant majority of the evidence suggests that time series momentum is a feature of financial markets and can form the basis of trading strategies that generate returns in excess of the risk free rate. The effect is found across all asset classes and consistently through time.

Evidence from the performance of CTAs supports this, at least when looking at the returns gross of fees. This conclusion relies on the reasonable assumption, with some supporting evidence, that time series momentum is the dominant trading strategy of CTAs.

There is little direct discussion of the excess return of time series momentum as an anomaly to the efficient market hypothesis, however standard pricing factors have little power to explain this returns.

A number of risk factors have been developed to capture the returns to alternative investment strategies. These have been shown to explain a portion of the return to both time series momentum and CTA funds but a statistically significant excess return remains in both cases.

An alternative stream of literature links investment returns to macro-economic factors, including measures of the level of risk in markets. Some explanatory relationships have been identified, but the investigations have not yet focused on time series momentum.

Behavioural finance theories suggest mechanisms to generate price continuations but these have been mainly applied to cross-sectional momentum and their application to time series momentum has not yet been explored.

Chapter Three

Is This Time Different? Trend-Following and Financial Crises

Abstract[6]

Following large positive returns in 2008, CTAs received increased attention and allocations from institutional investors. Subsequent performance has been below long term average. This has occurred in a period following the largest financial crisis since the Great Depression. In this article, using almost a century of data, the authors investigate what typically happens to the core strategy pursued by these funds post global financial crises. They also examine the time series behaviour of the markets traded by CTAs during these crisis periods. Their results show that in an extended period following financial crises, trend-following average returns are less than half those earned in no-crisis periods. Evidence from regional crises shows a similar pattern. They also find that futures markets do not display the strong time series predictability prevalent in no-crisis periods, resulting in relatively weak returns for trend-following strategies in the four years immediately following the start of a financial crisis.

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[6] This paper has been published in *The Journal of Alternative Investments*, Vol. 17, No. 2. The research reported in this paper has been presented at the following conferences; FMA Europe, Maastricht, FMA International, Nashville and QuantInvest, London, all 2014. Lead author, John O'Brien, co-author, Mark Hutchinson.

3. Is This Time Different? Trend-Following and Financial Crises

Following strong performance in 2008 the aggregate performance of trend-following Commodity Trading Advisor (CTA) funds has been relatively weak. From January 2009 to June 2013, the annualized return of the Newedge Trend Index was -0.8%, versus 8.0% over the prior five year period, while assets under management of CTAs grew from $206 billion to $331 billion.[7] [8] This has occurred during a period of slow recovery in the US and prolonged crisis in the Eurozone.

Understandably, investors in CTAs are now beginning to question their performance. Have markets changed post the 2008 financial crisis? Will these types of strategies ever work again? In this article, using almost a century of data on trend-following, we attempt to provide some guidance on these issues by empirically investigating the following research questions. Is what has happened to the performance of trend-following subsequent to the US subprime and Eurozone crises typical of what happens post a financial crisis? If yes, then what happens to price patterns in the futures markets traded by these funds to cause such poor performance during these turbulent periods?

Our results indicate that subsequent to a global financial crisis trend-following performance tends to be weak for four years on average. Comparing the performance of crisis and no-crisis periods, the average return in the first twenty-four months following the start of a crisis is one-third of the return earned in no-crisis periods, while the performance in the forty-eight after a crisis start is half that of no-crisis periods. Providing additional supporting evidence we find a similar effect when we examine portfolios formed of local assets during regional financial crises.

Looking at the changing time series dynamics of futures markets we find a breakdown in futures market return predictability during the crisis periods. In no-crisis periods, futures market returns exhibit strong correlations at lags of up to twelve months, whereas during crisis periods correlations are significantly reduced, and, in a number of cases,

[7] Source: BarclayHedge.
[8] For the systematic sub-category, AUM has grown from $163 billion to $261 billion.

turn negative. This lack of time series return predictability reduces the opportunity for trend-following to generate returns.

The literature on trend-following is typically focused on the performance of different variations of these strategies for particular markets in specific periods (see, for example, Erb and Harvey (2006), Miffre and Rallis (2007) and Fuertes *et al.* (2010) for commodities and Okunev and White (2003) and Menkhoff *et al.* (2012b) for currencies). Schneeweis *et al.* (2008) provide a comprehensive review. The evidence of these studies is generally positive on the performance of trend-following with positive Sharpe ratios and little correlation with traditional asset classes. We provide further evidence on the long term performance of trend-following strategies through an analysis of the performance of a multiple asset class portfolio.

Related literature focuses on identifying the risks faced by CTAs. In a highly cited study, Fung and Hsieh (2001) use a portfolio of options to capture the non-linear payoff from CTAs. More recent research focuses on both the longer term performance of these strategies (Hurst *et al.* (2012)), identifying why futures markets trend (Moskowitz *et al.* (2012)), and also examining the interaction between trend-following and value (Asness *et al.* (2013)). Our research identifies and analysis a further performance risk for investors: the poor performance of trend-following subsequent to a financial crisis.

Our finding on the differing performance of trend-following strategies in crisis and no-crisis periods is consistent with predictions from behavioural finance and evidence on cross-sectional momentum in different economic states. Behavioural models link momentum to investor overconfidence (Daniel *et al.* (1998)) and decreasing risk aversion (Hong and Stein (1999)), with both models leading to overreaction and return predictability in asset prices. Cooper *et al.* (2004) highlight how overconfidence should fall and risk aversion should increase following market declines. These effects lower the likelihood of overreactions, and consequently return predictability, in periods following a financial crisis under the models proposed by both Daniel *et al.* (1998) and Hong and Stein (1999). Cooper *et al.* (2004) find evidence to support both these predictions for cross-sectional momentum, finding the state (direction) of the market is critically important to the profitability of cross-sectional momentum strategies.

Finally, there is an emerging literature examining the performance of dynamic trading strategies during periods of financial crisis (see, for example, Brunnermeier *et al.* (2008), Melvin and Taylor (2009) and Menkhoff *et al.* (2012a)) and the potential crash risk to these strategies (Daniel and Moskowitz (2014)). We extend this literature on strategy risk by providing direct evidence of the performance characteristics of trend-following subsequent to financial crises.

In summary our paper makes three key contributions. First, we provide evidence on the long term performance of trend-following using a diversified multi-country multi-asset class portfolio using data beginning in the 1920s. Second, we are the first paper to provide direct evidence on the performance of trend-following during financial crises, analysing both global and regional crises. Third, we examine the underlying markets to identify the cause of the differing performance across crisis and no-crisis periods.

The remainder of the article is organised as follows: 1) we describe the dataset we use to create our trend-following portfolios and our sample of global and regional crises; 2) we describe the methodology we use to create our trend-following portfolios; 3) we provide results on the performance of trend-following during global financial crises; 4) we provides results on the performance of trend-following for regional financial crises; 5) we conclude with a discussion of our key findings.

3.1 Data and Sample

In this section we describe how we classify our sample into crisis and no-crisis periods and the data sources used in the analysis.

3.1.1 Sample Period

We consider both global and regional crises. As described below, we create a global portfolio to analyse the performance characteristics of trend-following during global crises and a series of regional portfolios to provide additional evidence from more localised crises. Accordingly we have two samples: one to cover the global portfolio and the second to cover regional portfolios.

Identifying a list of global and regional financial crises is problematic. For simplicity we use the list of crisis identified in two of the most highly cited studies of financial crises (Kindleberger and Aliber (2011) and Reinhart and Rogoff (2009)). Table 3.1 describes the list of global financial crisis examined. These are the Great Depression in1929, the 1973 Oil Crisis, the Third World Debt crisis of 1981, the Crash of October 1987, the bursting of the dot-com bubble in 2000, and the sub-prime/euro crisis beginning in

2007.[9][10] The start date for each crisis is considered to be the month following the equity market high preceding the crisis.

The regional crisis countries/regions (with year of inception in parenthesis) are Spain (1977); Norway (1987); Nordic (1989); Japan (1990); Mexico (1994); Asia (1997); Colombia (1997) and Argentina (2000). The list comprises crises identified by Kindleberger and Aliber (2011) and Reinhart and Rogoff (2009). All crises except Mexico are noted by Reinhart and Rogoff (2009), while Kindleberger and Aliber (2011) do not consider Spain, Norway, Nordic, Colombia and Argentina.

Table 3.1
Global Financial Crises: Dataset

Crisis	Start Date	Data Source
Great Depression	Oct-1929	GFD
Oil Crisis	Oct-1973	GFD
Third World Debt	Aug-1981	Exchange/MSCI/GFD
Black Monday	Oct-1987	Exchange/MSCI
Dotcom Bubble	Mar-2000	Exchange
Sub Prime/Euro	Jul-2007	Exchange

Note: Exchange: exchange traded futures contract. MSCI: Forward derived from MSCI data. GFD: Forward derived from Global Financial Data.

3.1.2 Futures Returns

The data set for the global analysis consists of twenty-one commodities, thirteen government bonds, twenty equity indices, and currency crosses derived from nine underlying rates (see Table 3.2 column 1 for the full list) covering a sample period from January 1921 to June 2013.[11] The data consists of a combination of exchange traded futures data and forward prices derived from historical data. The appendix provides a more detailed description of the data sources, which generally consists of DataStream/MSCI for the more recent prices (from 1980) and Global Financial Data for the older price histories.

[9] Two other additional crises were considered for inclusion in the study. Kindleberger and Aliber (2011) describe a currency crisis in the fifties and sixties in their list of financial crises. However, an examination of the details of this period shows it is a series of individual regional crises stretching over a decade and a half, and consequently unsuitable for inclusion in this study. A second possible candidate for inclusion is the period around 1990, with the collapse of the Japanese economy, an oil price spike and the first Iraq war. However, as it was not included in Kindleberger and Aliber (2011) or Reinhart and Rogoff (2009) as a global crisis, it is not included.

[10] We refer to crises using the start date, as defined by the equity market high.

[11] We exclude the period from January 1940 to December 1949 from our sample due to concerns about data accuracy around World War II.

The data for the regional crises is also sourced from DataStream/MSCI and Global Financial Data. All the return series in the regional analysis are forwards calculated from the underlying price series.[12] Table 3.3 column 5 lists the source for each of the underlying instruments. Risk free rates come from Global Financial Data while yields are calculated from total return indices for both equity indices and bonds.

The analyses in this article are based on continuous cumulative excess return series for each of the instruments. There are two methods used to create these series. Where a futures contract trades on an exchange the return series of the individual futures contracts are combined to produce a continuous excess return series. Where futures contracts are not available, forward prices are created by combining the underlying spot price, yield and risk free rate. These two approaches are discussed below.

3.1.2.1 Continuous Returns from Futures Contracts

Continuous return series are created from futures where daily price and volume data is available. We calculate the daily excess return of the most liquid contract. This is generally the front month or the next-nearest to delivery month. We select the most liquid contract as follows. At time, *t*, the average volume over the previous three trading days is measured for each of the live delivery dates. We select the contract with the highest volume to be recorded as the excess return for that day. To replicate the practicalities of rolling contracts, once we select a further delivery month we do not allow the excess return of nearer delivery months to be selected again.

3.1.2.2 Continuous Return Forward Prices

Where exchange traded futures are not available, excess return series are created from the underlying spot price, risk free rate and yield. The excess return from buying a forward at the start of a month and holding it to month end, er_1, is given by:

$$er_1 = (1 + r_1)\left(\frac{1 + q}{1 + r_f}\right)^{(1/12)} - 1 \qquad (3.1)$$

where r_1 is the spot price return for the month, r_f is the one month risk free rate, and q is the annualized yield. In order to ensure the comparability of synthetic forwards and actual exchange traded futures, a number of tests were carried out where exchange traded

[12] Exchange futures data is available for Japan but we use a consistent methodology across all countries for the regional analysis.

futures returns were replaced by synthetic forward returns. The series were typically almost perfectly correlated and in all cases results were close to identical.

3.1.3 Global Portfolio Descriptive Statistics

Table 3.2 columns 4 and 5 present summary statistics of the continuous return series used in our global sample. Typically excess returns are positive with the exception of some commodities with a negative roll yield (see Erb and Harvey (2006) and Gorton and Rouwenhorst (2006)).

Table 3.2
Descriptive Statistics

The table summarizes the key attributes of the instruments used in the study. Two start dates are included; the first is the start date for derived forward contracts and the second is the start date for exchange-traded future contracts. The performance of the instrument is summarizes by two measures; mean annual return and annual volatility. This is shown first for the full sample and then for the two year period after the start of a financial crisis. Currencies are quoted as local units per USD.

			Full Sample		Crisis Period	
	Start Date Derived	Start Date Exchange	Annualized Mean Return (%)	Annualized Volatility (%)	Annualized Mean Return (%)	Annualized Volatility (%)
Commodity Futures						
COCOA		Jan-80	-8.14	29.67	-1.42	35.60
COFFEE		Jan-80	-6.80	37.53	-11.88	35.71
COPPER		Oct-88	5.82	26.21	-8.94	30.90
CORN		Jan-80	-5.13	25.32	-12.99	30.03
COTTON		Jan-80	-3.62	26.36	-17.36	27.24
GAS OIL		Sep-03	13.39	30.88	-8.20	44.36
GOLD		Jan-80	3.25	17.98	0.45	20.96
LEAN HOGS		Jan-80	-2.93	25.10	-17.13	23.37
LIGHT CRUDE OIL		Mar-83	6.42	34.72	2.30	39.35
LIVE CATTLE		Jan-80	1.71	14.30	-0.81	14.71
NATURAL GAS		Apr-90	-12.09	58.26	-30.25	73.89
NY HEATING OIL		Jan-80	6.55	32.66	2.77	32.76
PALLADIUM		Jan-80	7.95	33.38	0.77	46.71
PLATINUM		Jan-80	0.04	25.04	-5.88	32.03
RBOB GASOLINE		Oct-05	7.60	34.77	-14.85	49.34
SILVER		Jan-80	-5.66	31.48	-9.53	30.87
SOYABEAN MEAL		Jan-80	4.23	26.33	10.91	29.72
SOYABEAN OIL		Jan-80	-2.91	26.27	-13.02	29.96
SOYABEANS		Jan-80	-0.47	23.64	-3.97	27.69
SUGAR		Jan-80	-5.87	39.34	5.01	45.11
WHEAT		Jan-80	-7.66	25.14	-13.18	26.78

Table 3.2 (Continued)
Descriptive Statistics

The table summarizes the key attributes of the instruments used in the study. Two start dates are included; the first is the start date for derived forward contracts and the second is the start date for exchange-traded future contracts. The performance of the instrument is summarizes by two measures; mean annual return and annual volatility. This is shown first for the full sample and then for the two year period after the start of a financial crisis. Currencies are quoted as local units per USD.

			Full Sample		**Crisis Period**	
	Start Date Derived	**Start Date Exchange**	**Annualized Mean Return (%)**	**Annualized Volatility (%)**	**Annualized Mean Return (%)**	**Annualized Volatility (%)**
Bond Futures						
Australia-10Y	Jan-20	Jun-85	0.44	6.83	-1.70	10.03
Australia-3Y		May-88	4.34	9.81	-0.53	9.61
Canada-10Y	Jan-50	Sep-89	1.22	6.26	3.57	9.49
US-5Y	Jan-20	May-88	0.89	4.54	3.48	5.88
US-2Y		Jun-90	1.72	1.74	3.85	1.97
US-10Y	Jan-20	May-82	1.21	6.10	3.99	7.95
US-30Y	Jan-20	Jan-80	1.12	9.13	3.88	11.64
Germany-5Y		Oct-91	3.01	3.25	2.47	3.73
Germany-30Y		Sep-05	5.28	12.48	4.30	10.97
Germany-2Y		Mar-97	0.99	1.38	1.00	1.82
Germany-10Y	Jan-50	Nov-90	2.18	5.08	3.87	5.63
Japan-10Y	Jan-20	Dec-86	1.99	5.09	1.62	5.92
UK-10Y	Jan-20	Nov-82	0.07	7.84	3.40	10.39
Equity Index Futures						
SPI 200 - Australia	Feb-20	May-00	4.38	15.89	-15.85	26.12
S&P TSX60- Canada	Jan-70	Nov-11	2.72	16.60	-10.70	21.93
Dow Jones-US		Oct-97	7.30	17.10	-11.03	23.64
NASDAQ 100 - US		Apr-96	6.28	28.50	-31.60	37.87
AEX - Netherlands	Jan-70	Jun-88	4.71	19.11	-8.80	23.46
CAC 40 France	Jan-70	Jun-92	2.91	20.46	-9.38	24.01
DAX - Germany	Jan-50	Apr-96	5.64	18.63	-8.66	22.48
MDAX -Germany		Mar-05	9.29	22.99	-29.06	33.09
HANG SENG - Hong Kong	Jan-70	Apr-97	10.70	33.67	-23.31	39.25
S&P Midcap- US		Feb-92	2.37	15.76	-13.65	18.01
NIKKIE 225 - Japan	Jan-50	Mar-99	6.01	20.39	-14.03	20.62
S&P 500 – US	Jan-20	Oct-90	4.89	19.12	-14.52	22.61
KOSPI 200 - Korea	Jan-65	Mar-05	9.04	27.69	2.56	27.97
FTSE 100- UK	Feb-20	Oct-88	4.28	16.80	-10.14	27.57
IBES 35 - Spain	Jan-70	Oct-97	0.80	21.02	-13.14	21.02
MIB – Italy	Oct-50	Nov-90	1.46	22.06	-23.00	23.72
Russell 2000 - US		Apr-07	2.23	23.93	-20.31	28.49
OMXS 30 - Sweden	Jan-70	Feb-92	6.43	22.19	1.70	25.90
SMI - Switzerland	Jan-70	Sep-99	5.11	16.64	-7.38	19.07
SMI Midcap - Switzerland		Sep-05	2.13	19.00	-27.11	26.40
Currency Forwards						
AUD/USD	Jan-73		-1.54	11.72	2.36	14.66
CAD/USD	Jan-73		-0.51	6.63	0.90	8.21
CHF/USD	Jan-73		-0.66	12.55	2.14	12.98
EUR/USD (DEM/USD)	Jan-73		0.28	11.20	5.78	12.13
GBP/USD	Jan-73		-0.69	10.34	6.56	10.94
JPY/USD	Jan-73		-0.02	11.42	5.90	12.49
NOK/USD	Jan-73		-1.38	10.79	3.66	10.79
NZD/USD	Jan-73		-1.80	12.64	6.94	15.95
SEK/USD	Jan-73		0.10	11.31	8.35	12.65

The different asset classes also have quite different volatilities with equity indices and commodities having much higher volatility than fixed income and currencies. Within asset classes fixed income has the largest cross-sectional differences in relative volatility with shorter term bond futures having significantly lower volatility than longer-term equivalents.

In Table 3.2, columns 6 and 7, we present summary statistics for the different continuous return series during financial crisis periods, defined as the two years after the start of the crisis. Contrasting these with the full sample statistics it is noteworthy that equity returns are negative across all equity indices and countries (except Sweden and Korea), bond returns are reasonably similar, commodity returns are mostly negative and all currencies suffer depreciation versus the U.S. dollar.

3.1.4 Regional Descriptive Statistics

Table 3.3 reports descriptive statistics for the regional crisis forward contracts. With the exception of Spain, we consider the crises start date as the prior local equity market high. As stock markets globally, including Spain, were in a bear market since the 1973 Oil Crisis, and the crisis is listed as occurring in 1977 by Reinhart and Rogoff (2009), we use January 1977 as the start date for Spain. Within the regional crisis a mixture of instruments is available. Equity index data is available for all crises, whereas government bond data is unavailable for Norway, Finland, Indonesia, Philippines, Colombia and Argentina. Currencies are included only for Spain, Norway, Nordic, Japan and Colombia as the other regions had currencies pegged to the dollar.

3.2 Methodology

In this section we describe how the methodology used to create the trend-following global and regional portfolios and to empirically test for changing behaviour of the underlying markets in crisis and no-crisis periods.

3.2.1 Trend-Following Portfolios

In order to investigate the performance of trading strategies, we analyse the return series of portfolios generated from momentum signals. These portfolios are created from diversified ranges of both instruments and momentum strategies. Each momentum signal is defined in terms of its look back period, k, such that if the cumulative excess return over the last k months is positive the momentum signal is +1, and if it is negative the signal is -1. The momentum signal for time t is

$$M_{t,k}^{i} = sign\left(\sum_{1}^{k} \log(1 + r_{t-k}^{i})\right) \tag{3.2}$$

Here, $M_{t,k}^{i}$ is the momentum of instrument i at time t formed with a look-back period of k months, and $r_{t-k}^{i}$is the excess return of instrument i at time t-k.[13]

Table 3.3
Regional Crises: Summary Statistics

The table lists the key features of the data sample used in analysing country crises. The crises are listed with start date and countries involved. The instruments used and their data source are then listed, with GDF representing Global Financial Data and D/M being MSCI via DataStream. The final columns summarize the performance of these instruments in term of annual return and annual volatility. The full sample period is an eight year span starting one year before the crisis. The crisis period represents a two-year period from the crisis start date. Short term interest rates sourced from GFD. Currencies are quoted as local units per USD.

Region	Start	Country	Instrument	Data Source	Full Sample Mean	Full Sample Vol.	Crisis Periods Mean	Crisis Periods Vol.
Spain	Jan-77	Spain	Equity	D/M	4.12	39.48	5.95	67.71
			Bond	GFD	-12.67	16.92	-6.71	19.17
			Currency	GFD	-5.01	9.77	-2.98	12.89
Norway	Oct-87	Norway	Equity	D/M	4.84	12.05	-2.81	18.16
			Currency	D/M	-2.35	26.80	-0.48	33.46
Nordic	May-89	Sweden	Equity	D/M	-4.67	10.62	-0.65	9.62
			Bond	D/M	3.72	25.28	-2.63	28.09
			Currency	D/M	0.32	10.07	-0.14	10.19
		Finland	Equity	D/M	-1.35	12.64	-1.51	8.88
			Currency	D/M	-3.35	28.07	-9.16	24.90
Japan	Feb-90	Japan	Equity	D/M	-2.86	13.28	-1.77	10.36
			Bond	D/M	-7.83	23.33	-7.77	29.46
			Currency	D/M	2.34	7.43	-0.01	8.34
Mexico	Mar-94	Mexico	Equity	D/M	-1.27	11.59	-1.86	10.89
			Bond	GFD	-2.61	28.25	-2.94	31.69
Asia	Mar-97	Hong Kong	Equity	D/M	-2.48	22.03	6.14	37.34
			Bond	GFD	-6.49	31.09	-3.21	47.19
		Indonesia	Equity	D/M	3.63	7.72	-0.09	13.01
		Korea	Equity	GFD	-16.63	44.73	-8.18	68.91
			Bond	GFD	-2.24	44.36	3.76	64.69
		Malaysia	Equity	D/M	4.59	8.42	1.88	13.31
			Bond	GFD	-7.67	37.77	-4.80	61.74
		Philippines	Equity	D/M	4.04	5.82	0.14	6.84
		Thailand	Equity	D/M	-21.28	32.27	-5.41	45.03
			Bond	GFD	-15.88	50.70	-2.31	77.16
Colombia	Dec-97	Colombia	Equity	D/M	9.83	17.52	3.32	27.55
			Currency	GFD	1.06	34.41	-11.44	44.29
Argentina	Apr-00	Argentina	Equity	D/M	3.91	9.29	0.47	10.54

[13] Using price return rather than excess return to calculate momentum produces almost identical results.

In order to take a diversified measure of momentum, we use the range of values of k from 1 to 12, so the diversified momentum measure for each instrument is[14]

$$M_t^i = \frac{1}{K} . \sum_{1}^{K} M_{t,k}^i \tag{3.3}$$

M_t^i is the momentum of instrument *i* at time *t* and K is the number of different look back periods. Each instrument is given a weight proportional to the diversified momentum signal, between +/- 1 and inversely proportional to its volatility, so the size of the position is,

$$w_t^i = M_t^i . \frac{V_T}{\sigma_t^i} \tag{3.4}$$

The weight, w_t^i , is the holding in instrument i at time t and σ_t^i is the corresponding volatility. The position is scaled by a target volatility, V_T. The choice of this is arbitrary but it is set at 40% (consistent with Moskowitz *et al.* (2012)) which allows the resulting portfolio return series to have a volatility level equivalent to those reported in the literature and market indices, facilitating comparison. Each position is then held for a period of one month so that the return series for an instrument is

$$m_t^i = er_t^i . w_t^i \tag{3.5}$$

Here m_t^i is the excess return of instrument *i*, in time period *t*.

The final stage of the process combines the return series of the individual instruments into a single return series representing the return of a diversified momentum strategy. A two-step process is used to generate the return series. First, the average return across assets in an asset class is calculated and the mean return of the asset classes is calculated. This has the effect of splitting risk equally among the four asset classes and then equally among assets within each class.

The excess return and momentum series are analysed as calendar month returns. When monthly return series are created from daily series, these are calculated as calendar month returns. For the regional crises, returns are examined from the perspective of a

[14] This method produces identical return series to the Moskowitz *et al.* (2012) methodology, although, Moskowitz *et al.* (2012) produce return series for each momentum strategy and then average these.

U.S. investor, with the currency exposure of the underlying investment assumed to be hedged and profit or loss converted to U.S. dollars at the end of the month[15][16].

3.2.2 Ex-ante Volatility

As volatility of the instruments in the universe varies from 2% to 50% (see Table 3.2) an ex-ante estimate of volatility is required to scale returns to allow for comparison of results across different assets. This is necessary for both portfolio construction and regression analysis. As in Moskowitz *et al.* (2012), we use an exponentially weighted squared daily returns model to estimate volatility. This model is similar to a univariate GARCH model. The annualized volatility for each instrument is calculated as:

$$\sigma_t = \sqrt{261 \sum_{i=0}^{\infty} (1-\delta)\delta^i (r_{t-1-i} - \overline{r_t})^2} \tag{3.6}$$

The parameter δ is chosen so that the centre of mass of the weights is 60 days, so data from the last sixty days carries equal weight to all data up to then. The same model is used for all instruments.[17]

3.2.3 Transaction Costs and Fees

In order to allow comparison with actual fund results, transaction costs and fees are included in the calculation of portfolio performance.[18]

We use the cost estimate model described by Hurst *et al.* (2012), outlined in Table 3.4, defining costs as a proportion of the nominal value traded. The transaction costs are a function of asset class and time period. The costs of trading different assets within the same class are assumed to be similar. The starting point for Hurst *et al.* (2012) is the cost model of a large investment management firm which is used to produce cost estimates for the most recent period (2002 - 2012). Based on Jones (2002), who shows that the level of costs remained constant from 1930 to 1980 and have fallen by about 80% subsequently, Hurst *et al.* (2012) derive estimates for earlier periods.

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[15] We do not include transaction costs for the currency hedging, but these are likely to have a negligible effect on returns.

[16] Our results are robust to this assumption. Analysing returns in local currency leads to almost identical conclusions on performance.

[17] In the case where only monthly data is available, δ is chosen to give a center of mass of three months.

[18] Transaction costs are included in all the results shown. Management fees are only included where specified.

Table 3.4
One-way Transaction Costs as a Percentage of Notional Traded, by Asset Class

	1900-1992	1993-2002	2003-2013
Equities	0.36%	0.12%	0.06%
Bonds	0.06%	0.02%	0.01%
Commodities	0.60%	0.20%	0.10%
Currencies	0.18%	0.06%	0.03%

Adapted from Hurst *et al.* (2012)

In general, these estimates are consistent with other literature. Significant falls in trading costs, in line with Jones (2002), are recorded by Aitken *et al.* (2004), Burnside *et al.* (2006) and Subrahmanyam (2007). Similarly, estimates of current futures trading costs in the literature tend to be in line with these estimates (see for example Locke and Venkatesh (1997), Burnside *et al.* (2006) and Szakmary *et al.* (2010)).

Management and incentive fees are applied where indicated. These are set at typical values (Hurst *et al.* (2012)) of 2% and 20% respectively. Incentive fees are calculated monthly and include a high watermark.

3.2.4 Time Series Behaviour of Markets

In order to examine why trend-following performance might vary across different time periods it is necessary to identify differences in the time series characteristics of the underlying futures markets between these periods.

Moskowitz *et al.* (2012) provide evidence on the time series predictability of futures markets, from 1965 to 2009, using regression analysis. Taking a similar approach to examine predictability, for each futures contract, *i*, we regress the excess return, er_t^i, on its lagged excess return, er_{t-l}^i. The univariate regressions are carried out with a lag, *l*, where *l* ranges from 1 to 24 months. All the observations for each lag are stacked to allow a pooled panel regression. Given the wide range of volatilities in the universe, observations are normalised using the lagged *ex-ante* volatility, σ_{t-1}^i. The regression equation then becomes:

$$\frac{er_t^i}{\sigma_{t-1}^i} = \alpha + \beta_1 \frac{er_{t-l-1}^i}{\sigma_{t-l-1}^i} + \varepsilon_t^i \qquad (3.7)$$

In comparing the regressions from crisis and no-crisis periods we focus on reporting the regression βs as, unlike the t statistics, the βs are insensitive to changes in sample size. Due to limited data size we are unable to draw statistically significance conclusions on the differences between individual βs in the crisis and no-crisis periods, however we are able to test for statistically significant differences in the cumulative βs.

In the following section, we present a number of analyses comparing market characteristics in crisis and no-crisis periods. Unfortunately, Kindleberger and Aliber (2011) and Reinhart and Rogoff (2009) do not provide guidance on the length or end date of each crisis. Rather than attempting to define when each individual crisis ends, we focus our analyses instead on two fixed time periods, twenty-four months and forty-eight months, post the prior equity market high as our "crisis periods". Data outside of these time intervals is consider "no-crisis periods". While we acknowledge that our sample of crises is heterogeneous and does not last for a fixed period of time, it is a reasonable assumption that the majority of the data within these fixed time intervals can be considered crisis period data and so an analysis of that data will produce results representative of a market crisis.

3.3 Results

We begin by focusing on the performance of the global portfolio and the time series behaviour of futures returns during financial crises before moving on to provide some evidence from the regional crisis periods.

3.3.1 Global Financial Crises

3.3.1.1 Portfolio Performance

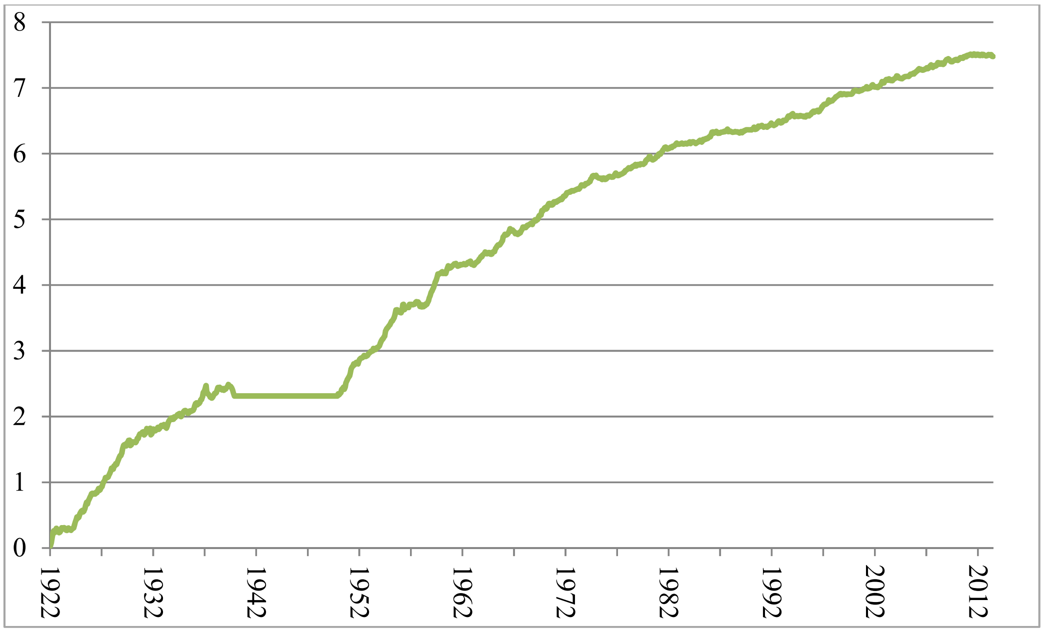
Before examining the performance of the trend-following portfolio in crisis periods, we review the performance of the portfolio across the full sample period. Figure 3.1 graphs the cumulative returns for the global portfolio from 1925 to 2013[19]. The average return net of fees is 12.1% with volatility of 11%.

[19] Including pre-1925 returns leads to larger performance differences between crisis and no-crisis periods. However, we exclude these portfolio returns as they are formed using volatility estimated generated using relatively short time series of asset returns.

Figure 3.1

Log Cumulative Return of Trend-Following Portfolio (January 1925 to June 2013)

The chart shows the log cumulative return of a diversified portfolio trend-following from 1925 to 2013. The results are shown net of transaction costs and fees (2% management fees and 20% performance fee). The decade around World War II, from January 1940 to December 1949, is omitted from the analysis due to concerns about data accuracy.



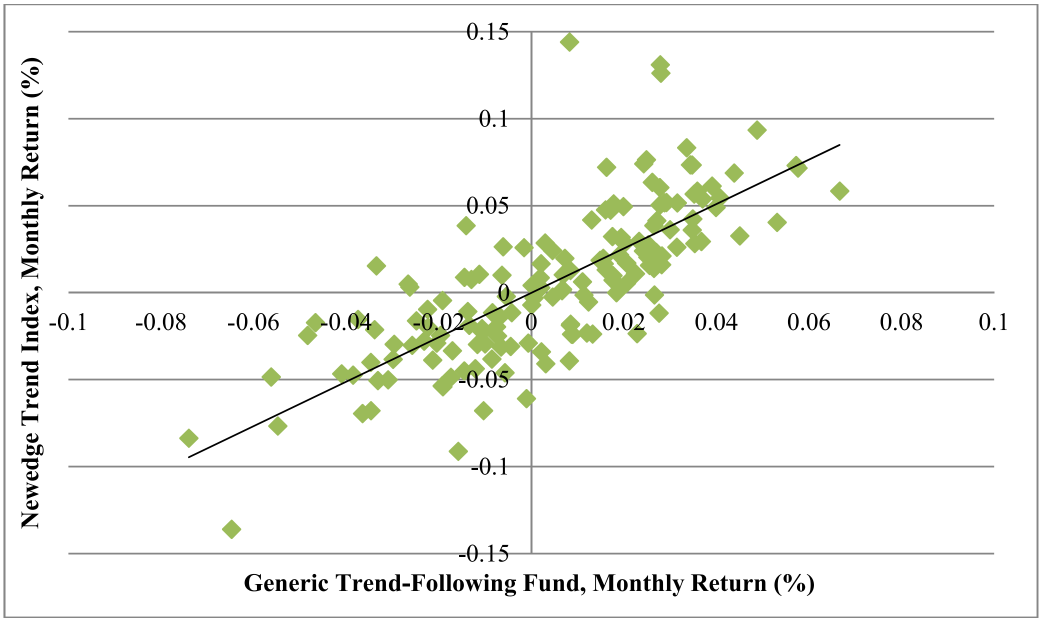
To ensure that the portfolio is capturing the characteristics of trend-following CTAs, we plot the returns of the portfolio against the returns of the Newedge Index of trend-following CTAs over the period 2000 to 2013 (Figure 3.2). The two series are highly correlated with a coefficient of 0.76.

Looking at performance in crisis and no-crisis periods, Table 3.5, Panel A, displays results for the full sample period from 1925 to 2013. Performance is reported for the global portfolio (net and gross of fees) and by asset class. This information is displayed graphically in Figure 3.3.

Column two reports the performance for each portfolio over the full period. The Sharpe ratio for the global portfolio is an impressive 1.1. Looking at individual asset classes the performance of Equity Indices and Government Bonds is better than the other two, Currencies and Commodities.

Figure 3.2
Comparison of Generic Trend-Following Performance with Newedge Trend Index, (January 2000 to June 2013)

The monthly performance of the generic trend-following portfolio generated in the research is plotted against the corresponding Newedge trend-following index performance. Generic Portfolio returns are net of trading costs, management fee (2%) and incentive fee (20%) and include a cash return.



Source: www.newedge.com

The performance comparison for the twenty-four month crisis period is reported in columns three to five. Column three reports crisis period performance, column four reports performance excluding the crisis period and column five reports the difference between column four and three. Columns six to eight report the same results, this time for a crisis period defined as lasting forty-eight months.

The results are very consistent. Comparing the performance of the first two years of trend-following subsequent to a crisis, the returns are far lower than in the no-crisis sample. At the full portfolio, level the average return in the first twenty-four months of a crisis is 4%, versus 13.6% in the no-crisis months. The return in the four year period from the start of a crisis averages 6%, versus 14.9% in the no-crisis sample. The results for equity index, government bonds and currency sub-portfolios are consistent with the global portfolio results over both the twenty-four month and forty-eight month crisis periods. The Sharpe ratio for the no-crisis period exceeds that for crisis period in each case and the excess ranges from 0.19 to 0.77. Only Commodities generate returns of a similar magnitude in crisis and no-crisis periods. The results for commodities are consistent with prior evidence on the lack of synchrony between the cycle of commodities and other asset classes (see, for example, Erb and Harvey (2006) and Gorton and Rouwenhorst (2006)).

Table 3.5
The Performance of Trend-Following during Financial Crises

The table shows the performance of trend-following strategies, at a diversified portfolio level and asset class level, from 1925-2013. All returns include trading costs. The performance is represented by the average excess return, volatility and Sharpe ratio. The first column represents the full sample period. Columns 2 & 3 break the performance into crisis and non-crisis periods assuming that a crisis last two years from the start date. Column 4 highlights the difference between the two. Columns 5-7 repeat the analysis in columns 2-4, but assume a crisis lasts four years.

Panel A: Full Sample (January 1925 to June 2013)

		Two Years			Four Years		
	All	**Crisis**	**No-crisis**	**Diff.**	**Crisis**	**No-crisis**	**Diff.**
FULL: Fees							
Return (%)	12.14	4.04	13.63	9.59	5.97	14.90	8.93
Volatility (%)	11.04	11.16	10.98	-0.18	10.92	11.03	0.11
Sharpe Ratio	1.10	0.36	1.24	0.88	0.55	1.35	0.80
FULL							
Return (%)	18.49	8.77	20.29	11.52	10.59	22.06	11.47
Volatility (%)	12.35	12.19	12.33	0.14	11.79	12.49	0.70
Sharpe Ratio	1.50	0.72	1.65	0.93	0.90	1.77	0.87
EQUITY							
Return (%)	5.13	3.47	5.44	1.97	3.68	5.76	2.08
Volatility (%)	4.78	4.91	4.75	-0.16	4.86	4.73	-0.13
Sharpe Ratio	1.07	0.71	1.14	0.43	0.76	1.22	0.46
BOND							
Return (%)	5.15	1.65	5.75	4.10	2.46	6.30	3.84
Volatility (%)	5.27	5.12	5.28	0.16	5.13	5.30	0.17
Sharpe Ratio	0.98	0.32	1.09	0.77	0.48	1.19	0.71
CURRENCY							
Return (%)	1.28	-0.02	1.71	1.73	0.99	1.60	0.61
Volatility (%)	3.28	3.57	3.17	-0.4	3.30	3.26	-0.04
Sharpe Ratio	0.39	-0.01	0.54	0.55	0.30	0.49	0.19
COMMODITY							
Return (%)	1.68	3.15	1.20	-1.95	2.74	0.60	-2.14
Volatility (%)	2.86	3.65	2.54	-1.11	3.27	2.36	-0.91
Sharpe Ratio	0.59	0.86	0.47	-0.39	0.84	0.26	-0.58

As a robustness check we repeat the analysis focusing on the period from 1980 to 2013, where exchange traded futures data is available. These results are reported in Table 3.5, Panel B.

Table 3.5 cont'd
The Performance of Trend-Following during Financial Crises

The table shows the performance of trend-following strategies, at a diversified portfolio level and asset class level, from 1980-2013. All returns include trading costs. The performance is represented by the average excess return, volatility and Sharpe ratio. The first column represents the full sample period. Columns 2 & 3 break the performance into crisis and non-crisis periods assuming that a crisis last two years from the start date. Column 4 highlights the difference between the two. Columns 5-7 repeat the analysis in columns 2-4, but assume a crisis lasts four years.

Panel B: Recent Sample (January 1980 to June 2013)

		Two Years			Four Years		
	All	**Crisis**	**No-crisis**	**Diff.**	**Crisis**	**No-crisis**	**Diff.**
FULL: Fees							
Return (%)	6.54	2.62	7.84	5.22	4.91	8.04	3.13
Volatility (%)	9.25	9.97	8.99	-0.98	9.45	9.06	-0.39
Sharpe Ratio	0.71	0.26	0.87	0.61	0.52	0.89	0.37
FULL							
Return (%)	11.22	6.73	12.71	5.98	9.21	13.08	3.87
Volatility (%)	10.12	10.74	9.90	-0.84	10.25	10.01	-0.24
Sharpe Ratio	1.11	0.63	1.28	0.65	0.90	1.31	0.41
EQUITY							
Return (%)	4.34	2.74	4.90	2.16	3.07	5.52	2.45
Volatility (%)	4.68	4.30	4.78	0.48	4.51	4.81	0.30
Sharpe Ratio	0.93	0.64	1.02	0.38	0.68	1.15	0.47
BOND							
Return (%)	3.81	0.69	4.79	4.10	2.12	5.37	3.25
Volatility (%)	5.53	5.23	5.60	0.37	5.23	5.77	0.54
Sharpe Ratio	0.69	0.13	0.86	0.73	0.41	0.93	0.52
CURRENCY							
Return (%)	1.18	0.26	1.45	1.19	1.20	1.17	-0.03
Volatility (%)	3.2	3.40	3.13	-0.27	3.28	3.13	-0.15
Sharpe Ratio	0.37	0.08	0.46	0.38	0.37	0.37	0.00
COMMODITY							
Return (%)	1.66	3.15	1.20	-1.95	2.74	0.60	-2.14
Volatility (%)	2.86	3.65	2.54	-1.11	3.27	2.36	-0.91
Sharpe Ratio	0.58	0.86	0.47	-0.39	0.84	0.26	-0.58

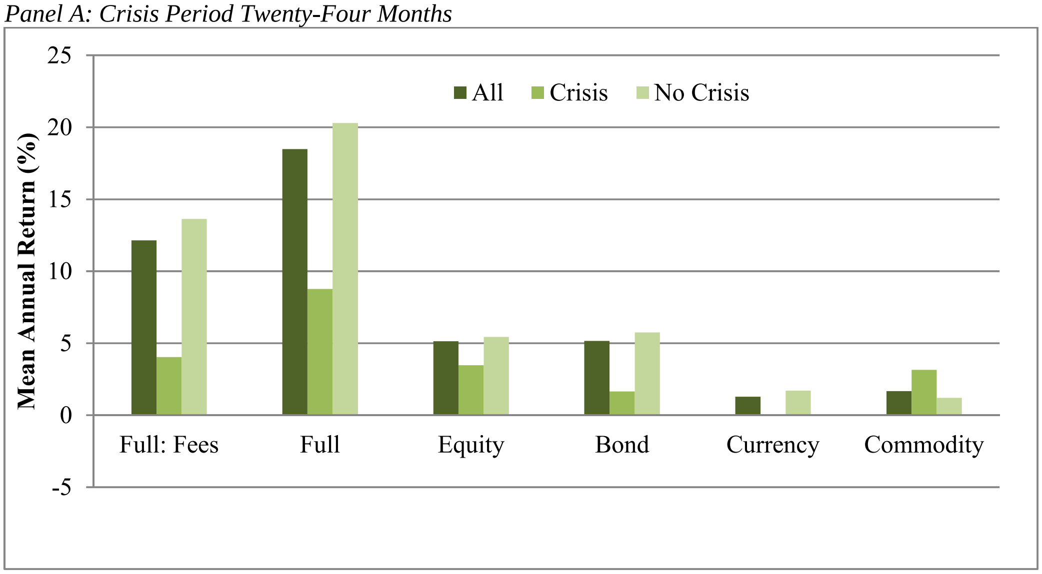
The results are remarkably consistent with Panel A. For a two year crisis period the full portfolio net of fees generates returns almost one third of those earned in no-crisis periods. The only exception is Currencies where four years into the crisis the performance differential is zero for the crisis and no-crisis returns.

Figure 3.3

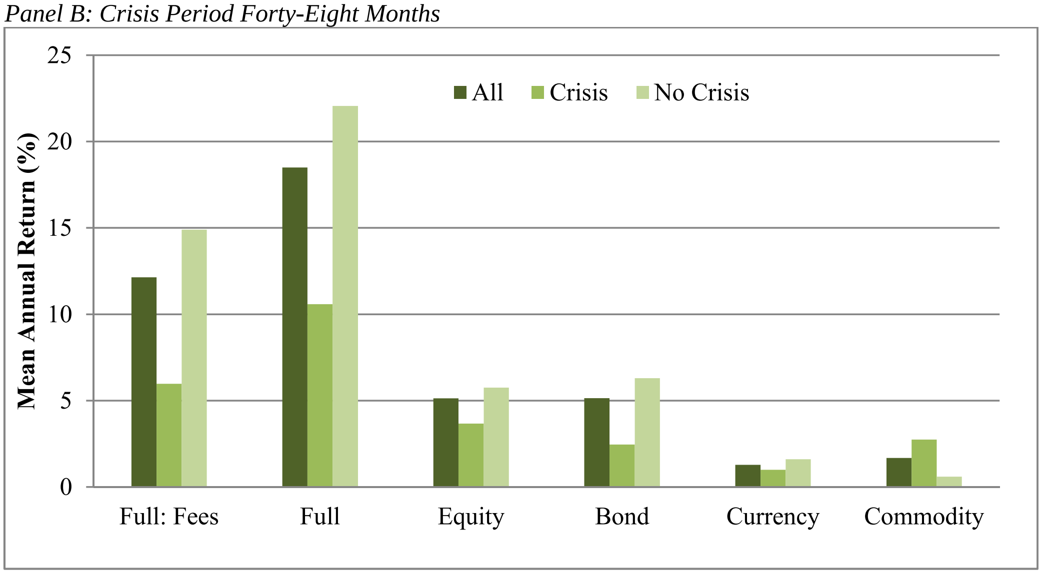
The Performance of Trend-Following during Financial Crises (Jan. 1925 to June 2013)

The chart shows the average annual performance of trend-following strategies, at a diversified portfolio level and asset class level, from 1925-2013. All returns include trading costs. Panel A assumes a twenty-four month crisis whereas Panel B assumes a forty-eight month crisis period

Panel A: Crisis Period Twenty-Four Months



Panel B: Crisis Period Forty-Eight Months



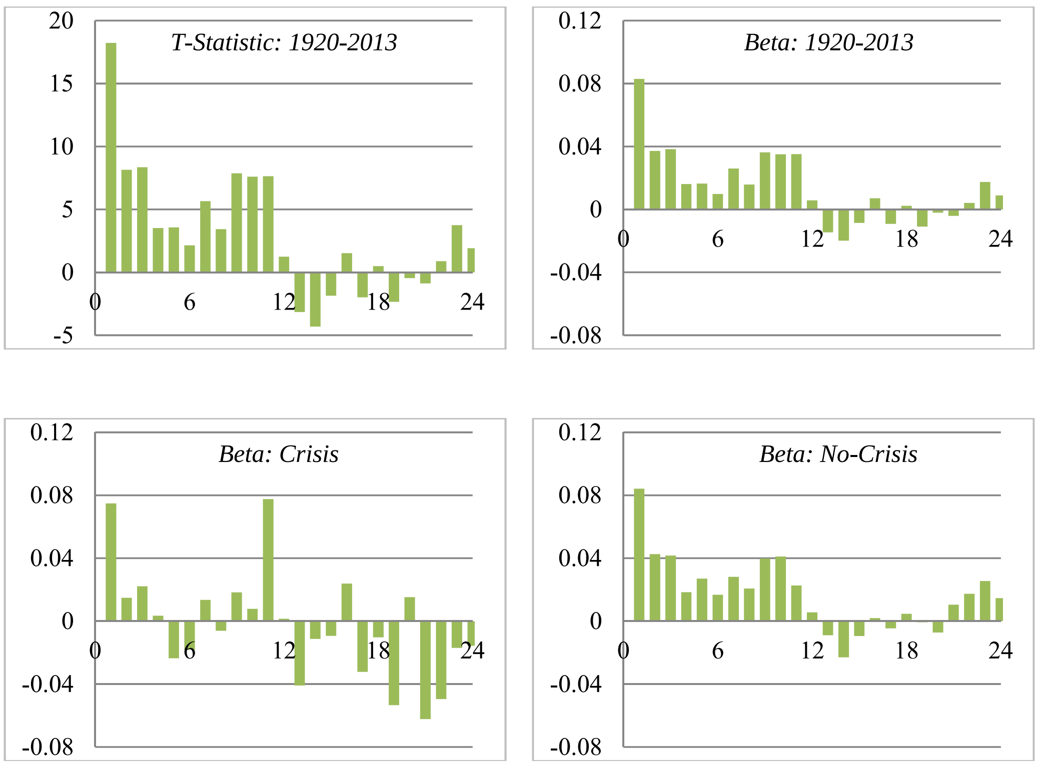
3.3.1.2 Time Series Effects

Next, we examine the predictability of these markets to establish whether there is a difference in the time series behaviour of futures markets between crisis and no-crisis periods.

Figure 3.4 reports results of these tests for the full sample. Consistent with Moskowitz *et al.* (2012), there is strong return continuation for the first twelve months, with limited evidence of subsequent reversals.

Figure 3.4
Time Series Correlation of Asset Prices, All Classes

Monthly excess returns of each instrument are regressed on lagged excess returns over a range of time horizons. The sample consists of data from 1921 to 2013 and the regression model is $er_t^i/\sigma_{t-1}^i = \alpha + \beta_1 er_{t-l-1}^i/\sigma_{t-l-1}^i + \varepsilon_t^i$. The top two graphs report the t-statistic and β_1 for lags from one month to twenty-four months. The sample is then split between crisis and no-crisis periods. Crisis periods are assumed to last two years from the start date and the β_1 reported for these.



When we next divide the sample into crisis and no-crisis periods, the different dynamics become very apparent. Within crisis periods the return continuation disappears. Reversals occur in months five, six and eight and the beta of continuation months is smaller. With significantly weaker relationship between return months the opportunities for profitable trend-following are diminished. Excluding crisis periods, the pattern of strong continuations becomes very evident. Unlike crisis periods, the no-crisis periods provide plenty of profitable opportunities for trend-followers.[20]

[20] Repeating the analysis using the longer crisis period definition provides very similar results.

To examine time series characteristics of the different asset classes we repeat the analysis for each. Figure 3.5 reports betas for crisis and no-crisis periods by asset class. Equity indices, government bonds and currencies have strong return continuation out to twelve months in no-crisis periods, whereas there are reversals in at least two of the first six months evident in the crisis periods. The only exception is commodities, which have strong return continuations for the first five months into the crisis, before reversing. This explains why the crisis returns are higher than no-crises returns for commodities, as seen in Table 3.5.

An alternative view of the regressions is presented in Figure 3.6. Here, the cumulative sum of the regression coefficients (Betas) is shown, along with its 95% confidence interval, for crisis and no-crisis periods. This is shown for the full universe of assets and also by asset class.

The degradation in autocorrelation as markets move to crisis periods is evident. After twelve months, the cumulative beta for the no-crisis period is significantly (95% confidence level) above the crisis period for the full portfolio, equity indices and currencies, while the difference for government bonds is also evident but falls short of statistical significance. The commodity market is, as expected, the exception, with similar crisis and no-crisis results.

Figure 3.5
Time Series Correlation by Asset Class: Regression Beta

Monthly excess returns of each instrument are regressed on lagged excess returns over a range of time horizons. The sample consists of data from 1921 to 2013 and the regression model is $er_t^i/\sigma_{t-1}^i = \alpha + \beta_1 er_{t-l-1}^i/\sigma_{t-l-1}^i + \varepsilon_t^i$. The sample is divided by asset class and then between crisis and no-crisis market periods, with crises periods are assumed to last two years from the start date. The β_1 for each lag from one month to twenty-four months is reported for each asset class for crisis and no-crisis periods.

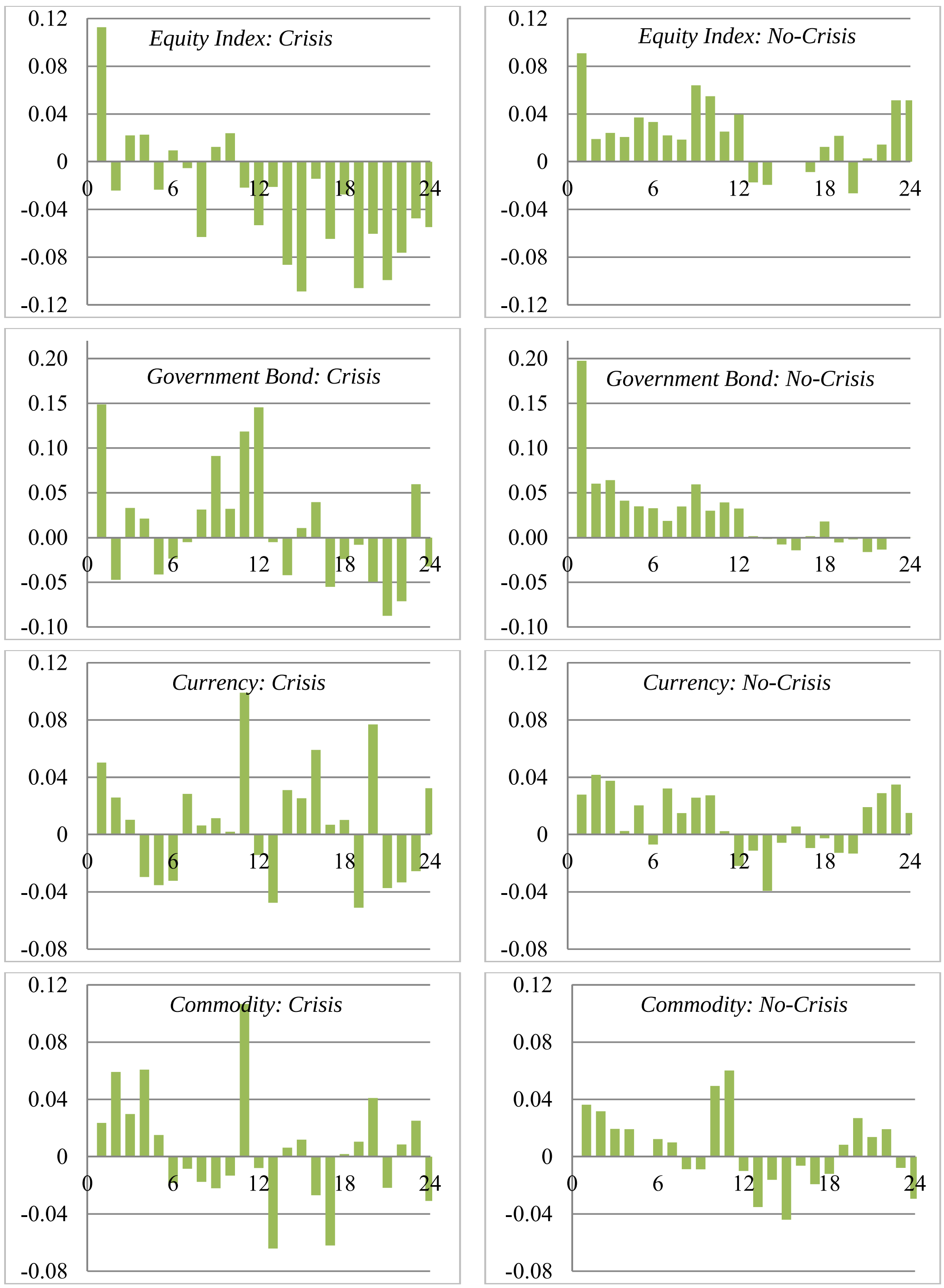
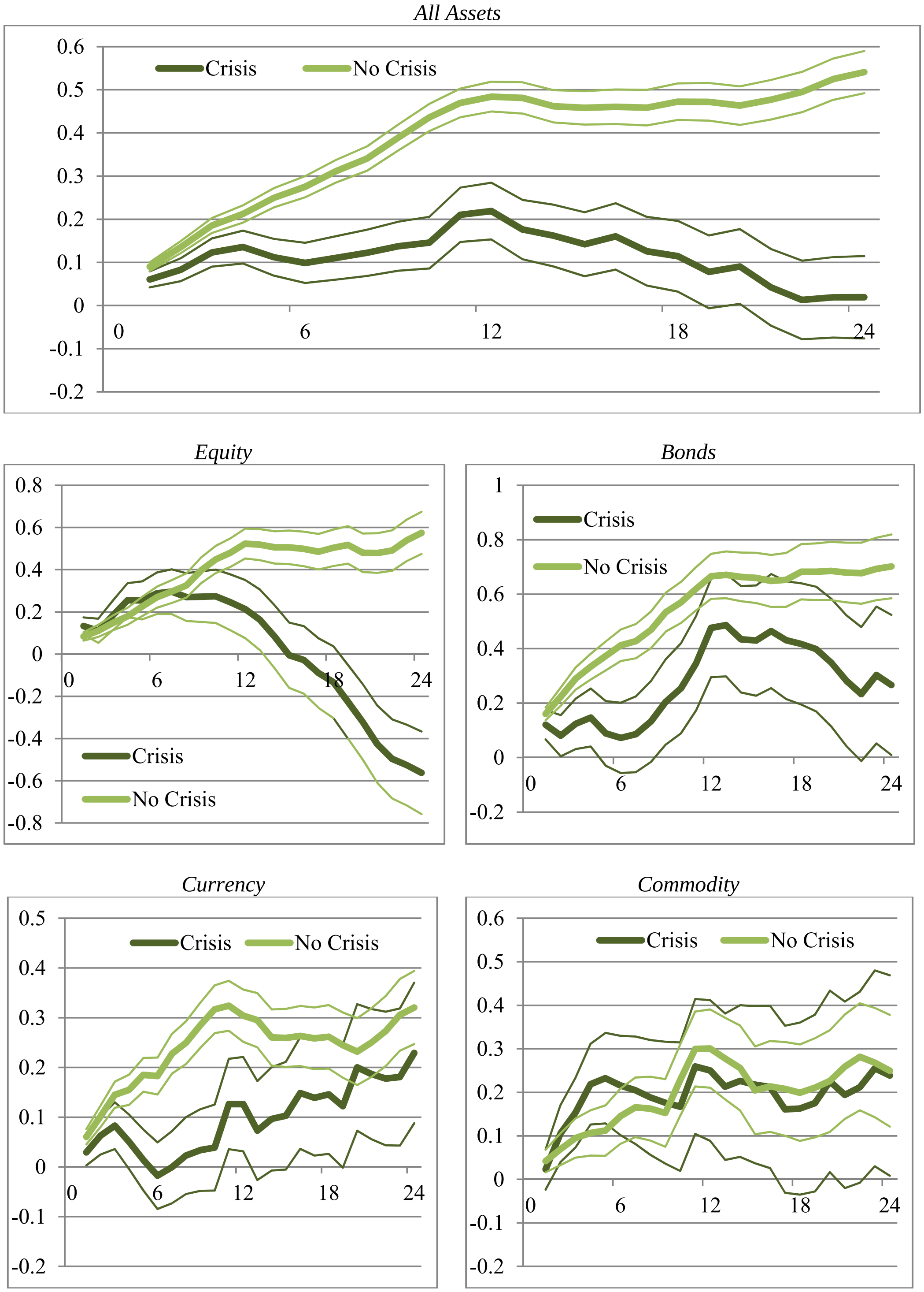


Figure 3.6

Time Series Correlation: Cumulative Beta with Confidence Interval

The cumulative regression coefficients from a series of lagged regressions, along with their 95% confidence interval are plotted. Monthly excess returns are regressed on lagged excess returns over a range of time horizons. The sample consists of data from 1921 to 2013 and the regression model is $er_t^i/\sigma_{t-1}^i = \alpha + \beta_1 er_{t-l-1}^i/\sigma_{t-l-1}^i + \varepsilon_t^i$. Each graph splits the sample between crisis and no-crisis periods. A crisis period is assumed to last two years from the start date.



3.3.2 Regional Financial Crises Performance

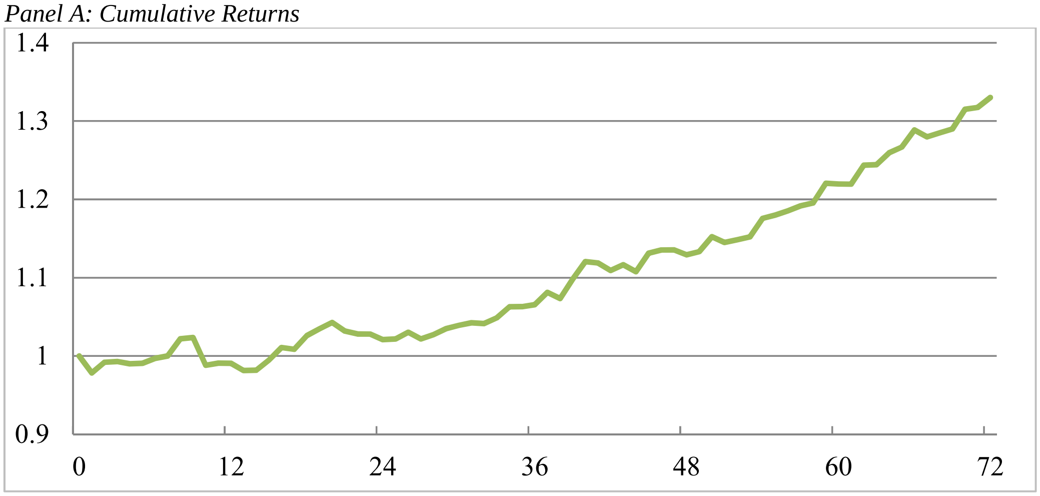
Given there are only six global crisis we also provide additional evidence using a range of regional crises. Summary results for the regional crises are reported in Figure 3.7. Panel A displays the cumulative returns of an equally weighted portfolio made up of the eight individual financial crisis portfolios, all aligned with the prior equity market high at month 0. Performance is relatively weak for the first two to three years into the crisis.

Figure 3.7

Performance of a Trend-Following Portfolio following a Regional Financial Crisis

The chart shows the mean combined performance of the eight regional crises, each of which are aligned on the local stock market high. The table summarizes the performance by year. For each year, the mean return and mean volatility of the eight crises are shown. These are accompanied by the best and worst individual performance and the highest and lowest individual volatility.

Panel A: Cumulative Returns



Panel B: Summary Performance Statistics

	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6
Average Return (%)	-1.25	2.87	4.41	6.03	7.89	9.07
Best (%)	11.48	8.10	17.02	27.24	17.77	22.81
Worst (%)	-14.71	-8.39	-3.48	-6.94	-2.45	-5.23
Average Volatility (%)	11.80	7.60	4.75	8.84	8.13	7.02
Highest (%)	17.81	17.45	8.15	14.43	15.11	11.74
Lowest (%)	5.02	3.01	3.19	4.19	4.35	2.69

Looking next at the summary performance statistics of the individual crisis reported in Panel B, it is evident that there is significant cross-sectional deviation across crises performance. For example, in year one, when the average return across crises is -1.3%, the range of crisis returns was from -14.7% to +11.5% Again in year two, the average crises return is 2.9% with a range of outcomes, from -8.4% to 8.1%. In years four to six average returns gradually increase up to 9%, but in each year the range remains wide and at least one of the crisis portfolios generates negative returns.

3.3.3 A Comparison of Crises

The heterogeneous nature of the global crises makes it difficult to compare individual crises. A number of features however can be highlighted. Figure 3.8, Panel A, graphs the cumulative returns for the trend-following portfolio for each crisis period. The crises can be loosely classified into two groups, those that develop quite rapidly (1929, 1987 and 2000) and those that develop more gradually (1974, 1981 and 2007). The first group tend to start with a period of very poor trend-following performance, generally due to losses in the equity index sub-portfolio, as the equity indices reverse quite sharply. The crises that develop more slowly allow time for the trend-following signals to adjust to the new market direction before the crisis fully develops, resulting in short run profitability.

The poor performance during market crises is generally due to extended periods in which cumulative returns move sideways rather than experiencing significant drawdowns. These periods are characteristic of all the crises we examined. The longest period each crisis undergoes without generating an excess return is presented in Figure 3.8, Panel B. This ranges from 18 months (2000) to 54 months (1987) and averages three years. It is notable that this extended period of weak performance begins at different intervals in the crises.

It is only possible to comment on regional crises at an aggregate level due to the scale of heterogeneity in the individual results. The general pattern, a period of poor performance followed by an improvement in performance, is consistent with the return series of the global portfolios. Here the aggregate excess returns are close to zero in the first two years with performance beginning to improve through years three and four.

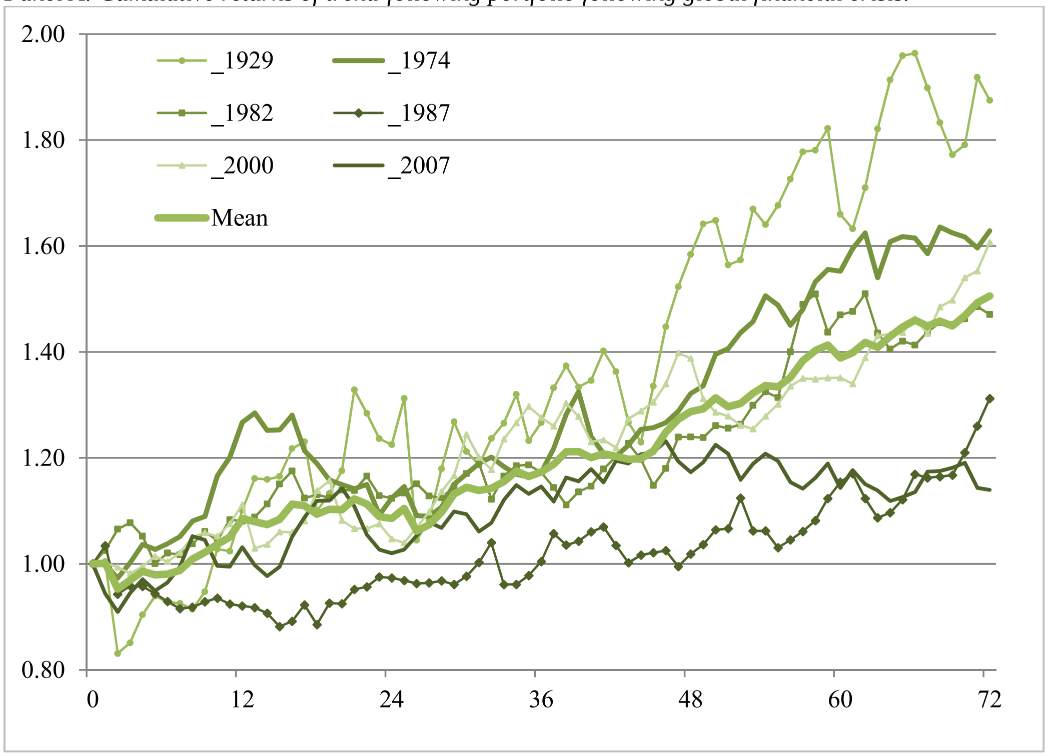
Taken together the results reported in this section of the paper provide clear evidence on the effect of financial crises both on trend-following performance and the underlying markets traded by these funds. The performance of these types of strategies is much weaker in crisis periods, where performance can be as little as one-third of that in normal market conditions. This result is supported by our evidence for regional crises, though the effect seems to be more short lived. In our analysis of the underlying markets, our empirical evidence indicates a breakdown in the time series predictability, pervasive in normal market conditions, on which trend-following relies.

Figure 3.8

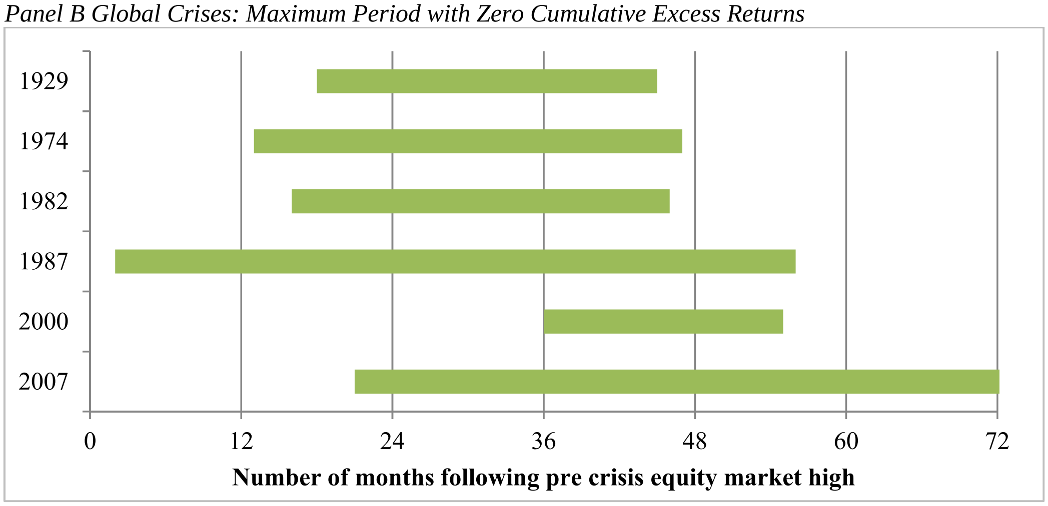
Comparison of Trend-Following performance after Global Financial Crises

Panel A shows the cumulative return of each global crisis and the mean combined performance of the six global crises, each of which is aligned on the pre-crisis stock market high. Panel B displays the length of the maximum period that the trend-following portfolio generates zero cumulative excess returns for each crisis.

Panel A: Cumulative returns of trend-following portfolio following global financial crisis.



Panel B Global Crises: Maximum Period with Zero Cumulative Excess Returns



3.4 Conclusions

In conclusion, this article has taken an extensive look at the long term performance of trend-following strategies, how those strategies perform during regional and global financial crises periods and what happens to the underlying markets traded by funds pursuing these strategies.

Our analysis of the long term performance of trend-following strategies using a diversified global multiple asset class portfolio from 1925 to 2013, suggests that these strategies have produced consistently high returns through time. Despite the below average recent performance of trend-following funds, this should give investors in funds employing these types of strategies some comfort.

Looking next at the performance of these strategies during financial crises the evidence is consistent. These strategies typically underperform for an extended period, on average four years, following a crisis. Performance outside these crisis periods is more than double the crisis returns.

Repeating the analysis focusing on regional crises, the results are consistent with the global performance. Although individual crises differ significantly, the pattern of a period of poor performance followed by reversion to long term norms is repeated, although here performance begins to pick up during the third year after the crisis.

We find significant differences in the time series dynamics of the underlying markets between crisis and no-crisis periods. In futures markets there are strong autocorrelation in time series returns of instrument at lags of one to twelve months which drive trend-following returns. By dividing the data between crisis and no-crisis periods, we find that this relationship is significantly diminished during periods of financial crisis. This has the consequence of significantly reducing the returns of the trend-following strategy.

Our research leads to a key question which remains unanswered - What happens to cause this break down in the time series behaviour of futures markets following a financial crisis?

Existing behavioural finance theories provide some predictions that our results support. For example Daniel *et al.* (1998) and Hong and Stein (1999) link serial correlation in asset returns to increases in overconfidence and decreased risk aversion of investors.

Precisely the opposite conditions occur in a financial crisis, with investor confidence falling and risk aversion increasing. Under both models, opportunities for generating trend-following returns should decrease in these periods.

Also, as noted by Daniel *et al.* (2002), governments have an increased tendency to intervene in financial markets during crises, resulting in discontinuities in price patterns. The Federal Reserve's support of Bear Sterns in March 2008 (Melvin and Taylor (2009)) and the intervention by the Hong Kong Monetary Authority in Hang Seng futures in 1998 (Bhanot and Kadapakkam (2006)) both caused sharp reversals in their respective markets. The frequency, effect and consequences of these interventions for trend-following require further research.

Finally, hedging pressure has long been recognised as having a role in the price setting mechanism of commodity markets. (De Roon *et al.* 2000) demonstrates that hedging pressure has a significant effect on the futures risk premia, so changing dynamics in hedging pressure during crisis may cause changes in market characteristics. More explicitly, Moskowitz *et al.* (2012) link the returns of trend-following with the cost of hedging, as speculators (trend-followers) capture a premium from hedgers. It is possible that, as hedgers benefit from positions in a crisis, the premia normally paid by hedgers to speculators are reversed.

It should be stressed that while the above points suggest mechanisms by which market states may differ from crisis to no-crisis periods, we do not present evidence that these changes occur, or if they do, that they are the cause the time series effects that we have identified in our analysis. Significant further research is needed to fully understand their effects on the markets and on the return characteristics of time series momentum.

3.A Appendix: Data Sources

3.A.1 Equity Indices

The universe of equity indices has twenty components. Fourteen of these consist of data from developed markets, with future prices available from Datastream starting at various dates from January 1980 and derived forward prices generated from data from Global Financial Data prior to that. In each case Global Financial Data provides a total return index, which allows the yield to be calculated. This group consists of Australia (SPI 200), Canada (TSX 60), Netherlands (AEX), France (CAC 40), Germany (DAX), Hong Kong (Hang Seng), Korea (KOSPI 200), Japan (Nikkei 225), United States (S&P 500), United Kingdom (FTSE 100), Spain (IBEX 35), Italy (MIB), Sweden (OMX 30) and Switzerland (SMI).

The six additional indices are the three mid cap indices (Germany, Switzerland and United States) and three alternative indices for the U.S. (Dow Jones, Russell 2000 and NASDAQ 100). We only include exchange traded future contract data for these indices.

3.A.2 Bond Indices

A total of thirteen government bond indices from six countries are used. Australia (3 and 10 year), Canada (10 year), United States (2, 5, 10 and 30 year), Germany (2, 5, 10 and 30 year), Japan (10 year) and United Kingdom (10 year). Exchange data for these is from Datastream, starting on a variety of dates from January 1980. The data for eight of these is extended backwards using total return indices and short term yields from Global Financial Data. As the Australian bond futures are quoted as (100-interest rate), these returns were normalized to facilitate the combination of synthetic and market-price series.

3.A.3 Currencies

The universe of currency forwards consists of ten currencies. Forwards are created for all currency pairs from spot data and short term interest rates. The spot rates are sources from Datastream/MSCI from 1980 and, prior to that, from Global Financial Data. Although data is available back to 1920, currencies are only considered for inclusion and statistics provided from the end of the Bretton-Woods fixed rate system in 1971. The Euro and German Mark are spliced into one time series. The currencies included are Australian Dollar, Canada Dollar, Euro (German Mark), Norwegian Krone, New

Zealand Dollar, Sweden Krona, Swiss Franc, United Kingdom Pound and United States Dollar.

3.A.4 Commodities

There are twenty-one commodities traded: Copper, Gold and Silver (COMEX), Light Crude Oil, Natural Gas, NY Heating Oil, Palladium, Platinum and RBOB Gasoline (NYMEX), Cocoa, Coffee, Cotton, Gas Oil and Sugar (ICE), Corn, Soya Bean Oil, Soya Bean Meal, Soya Beans and Wheat (CME) and Lean Hogs and Live Cattle (CBOT). The commodity data is entirely based on prices of exchange traded futures, provided by DataStream. As cost of carry data is unavailable, it is not possible to accurately estimate forward prices prior to the availability of exchange traded futures.

3.A.5 Risk Free Rates

Short term interest rates are sourced from Global Financial Data. The one month interbank rate (LIBOR or equivalent) is the preferred rate. When this is not available, the closest available interbank rate was used, and finally the central bank base rate.

3.B Appendix: Supplementary Analysis

3.B.1 Test Statistics

This section extends statistical analysis presented earlier in the chapter. The test statistics for the differences of mean returns in crisis and no-crisis periods are presented in Table 3.6. The test statistics of the slope coefficient of the regressions of lagged returns are presented in Figures 3.9 & 3.10. The values presented in these figures for crisis and no-crisis periods are not directly comparable due to different sample sizes.

Table 3.6
The Performance of Trend-Following during Financial Crises

The table shows the performance of trend-following strategies, at a diversified portfolio level and asset class level, from 1925-2013. All returns include trading costs. The performance is represented by the average excess return, volatility and Sharpe ratio. The test statistics of the return difference between crisis and no-crisis periods are presented in brackets. The first column represents the full sample period. Columns 2 & 3 break the performance into crisis and non-crisis periods assuming that a crisis last two years from the start date. Column 4 highlights the difference between the two. Columns 5-7 repeat the analysis in columns 2-4, but assume a crisis lasts four years.

Panel A: Full Sample (January 1925 to June 2013)

		Two Years			Four Years		
	All	**Crisis**	**No-crisis**	**Diff.**	**Crisis**	**No-crisis**	**Diff.**
FULL: Fees							
Return (%)	12.14	4.04	13.63	9.59	5.97	14.90	8.93
Volatility (%)	11.04	11.16	10.98	-0.18	10.92	11.03	0.11
Sharpe Ratio	1.10	0.36	1.24	0.88	0.55	1.35	0.80
				(2.78)			(3.31)
FULL							
Return (%)	18.49	8.77	20.29	11.52	10.59	22.06	11.47
Volatility (%)	12.35	12.19	12.33	0.14	11.79	12.49	0.70
Sharpe Ratio	1.50	0.72	1.65	0.93	0.90	1.77	0.87
				(2.98)			(3.81)
EQUITY							
Return (%)	5.13	3.47	5.44	1.97	3.68	5.76	2.08
Volatility (%)	4.78	4.91	4.75	-0.16	4.86	4.73	-0.13
Sharpe Ratio	1.07	0.71	1.14	0.43	0.76	1.22	0.46
				(1.32)			(1.78)
BOND							
Return (%)	5.15	1.65	5.75	4.10	2.46	6.30	3.84
Volatility (%)	5.27	5.12	5.28	0.16	5.13	5.30	0.17
Sharpe Ratio	0.98	0.32	1.09	0.77	0.48	1.19	0.71
				(2.49)			(2.99)
CURRENCY							
Return (%)	1.28	-0.02	1.71	1.73	0.99	1.60	0.61
Volatility (%)	3.28	3.57	3.17	-0.4	3.30	3.26	-0.04
Sharpe Ratio	0.39	-0.01	0.54	0.55	0.30	0.49	0.19
				(1.42)			(0.59)
COMMODITY							
Return (%)	1.68	3.15	1.20	-1.95	2.74	0.60	-2.14
Volatility (%)	2.86	3.65	2.54	-1.11	3.27	2.36	-0.91
Sharpe Ratio	0.59	0.86	0.47	-0.39	0.84	0.26	-0.58
				(-1.77)			(-2.07)

Table 3.6 cont'd
The Performance of Trend-Following during Financial Crises

The table shows the performance of trend-following strategies, at a diversified portfolio level and asset class level, from 1980-2013. All returns include trading costs. The performance is represented by the average excess return, volatility and Sharpe ratio. The test statistics of the return difference between crisis and no-crisis periods are presented in brackets. The first column represents the full sample period. Columns 2 & 3 break the performance into crisis and non-crisis periods assuming that a crisis last two years from the start date. Column 4 highlights the difference between the two. Columns 5-7 repeat the analysis in columns 2-4, but assume a crisis lasts four years.

Panel B: Recent Sample (January 1980 to June 2013)

		Two Years			Four Years		
	All	**Crisis**	**No-crisis**	**Diff.**	**Crisis**	**No-crisis**	**Diff.**
FULL: Fees							
Return (%)	6.54	2.62	7.84	5.22	4.91	8.04	3.13
Volatility (%)	9.25	9.97	8.99	-0.98	9.45	9.06	-0.39
Sharpe Ratio	0.71	0.26	0.87	0.61	0.52	0.89	0.37
				(1.49)			(0.96)
FULL							
Return (%)	11.22	6.73	12.71	5.98	9.21	13.08	3.87
Volatility (%)	10.12	10.74	9.90	-0.84	10.25	10.01	-0.24
Sharpe Ratio	1.11	0.63	1.28	0.65	0.90	1.31	0.41
				(1.56)			(1.08)
EQUITY							
Return (%)	4.34	2.74	4.90	2.16	3.07	5.52	2.45
Volatility (%)	4.68	4.30	4.78	0.48	4.51	4.81	0.30
Sharpe Ratio	0.93	0.64	1.02	0.38	0.68	1.15	0.47
				(0.83)			(1.50)
BOND							
Return (%)	3.81	0.69	4.79	4.10	2.12	5.37	3.25
Volatility (%)	5.53	5.23	5.60	0.37	5.23	5.77	0.54
Sharpe Ratio	0.69	0.13	0.86	0.73	0.41	0.93	0.52
				(1.98)			(1.69)
CURRENCY							
Return (%)	1.18	0.26	1.45	1.19	1.20	1.17	-0.03
Volatility (%)	3.2	3.40	3.13	-0.27	3.28	3.13	-0.15
Sharpe Ratio	0.37	0.08	0.46	0.38	0.37	0.37	0.00
				(0.98)			(-0.03)
COMMODITY							
Return (%)	1.66	3.15	1.20	-1.95	2.74	0.60	-2.14
Volatility (%)	2.86	3.65	2.54	-1.11	3.27	2.36	-0.91
Sharpe Ratio	0.58	0.86	0.47	-0.39	0.84	0.26	-0.58
				(-1.77)			(-2.07)

Figure 3.9
Time Series Correlation of Asset Prices, All Classes

Monthly excess returns of each instrument are regressed on lagged excess returns over a range of time horizons. The sample consists of data from 1921 to 2013 and the regression model is $er_t^i/\sigma_{t-1}^i = \alpha + \beta_1 er_{t-l-1}^i/\sigma_{t-l-1}^i + \varepsilon_t^i$. The top two graphs report the t-statistic and β_1 for lags from one to twenty-four months. The sample is then split between crisis and no-crisis periods. The values of β_1 and its test statistic are reported for the two periods. Crisis periods are assumed to last two years from the start date.

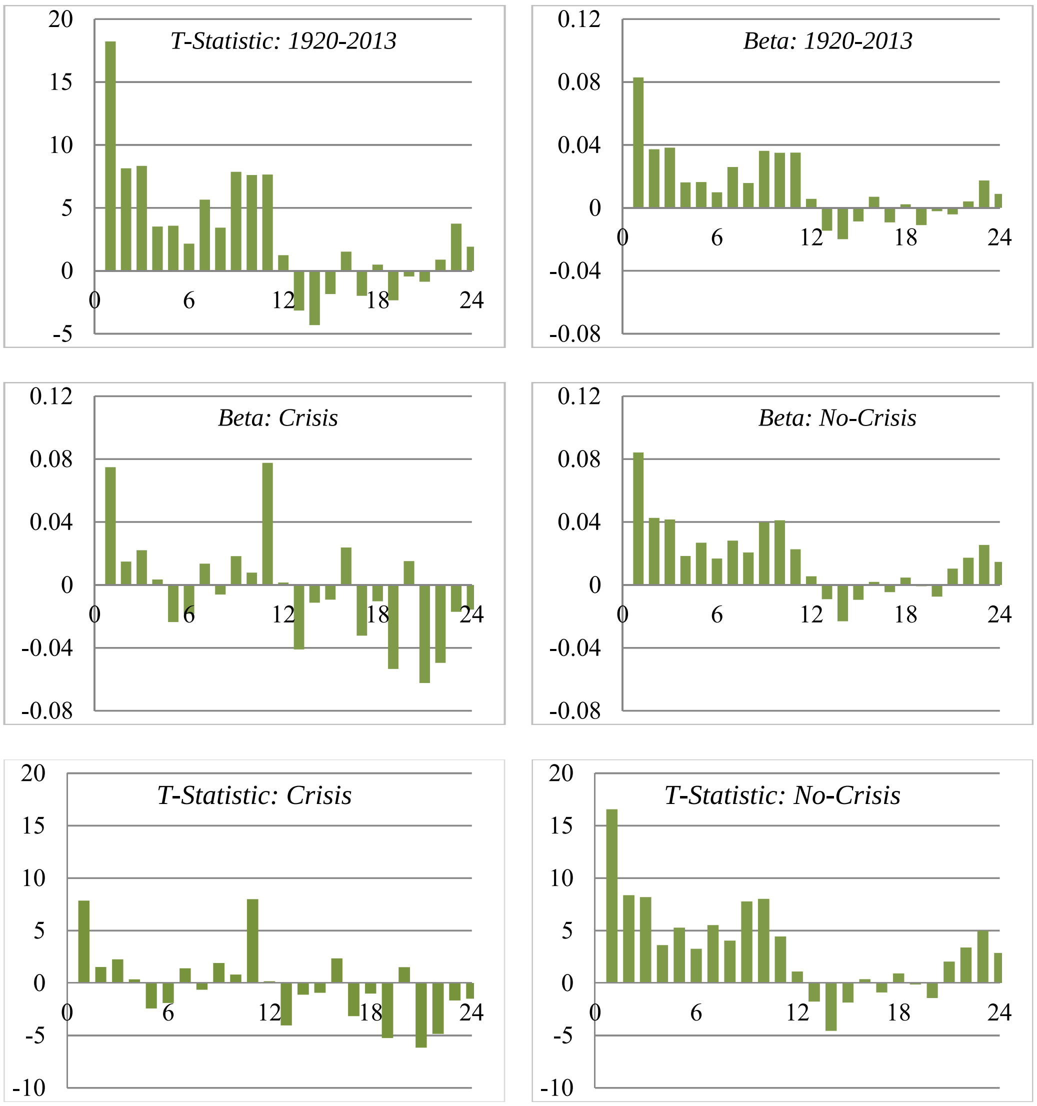
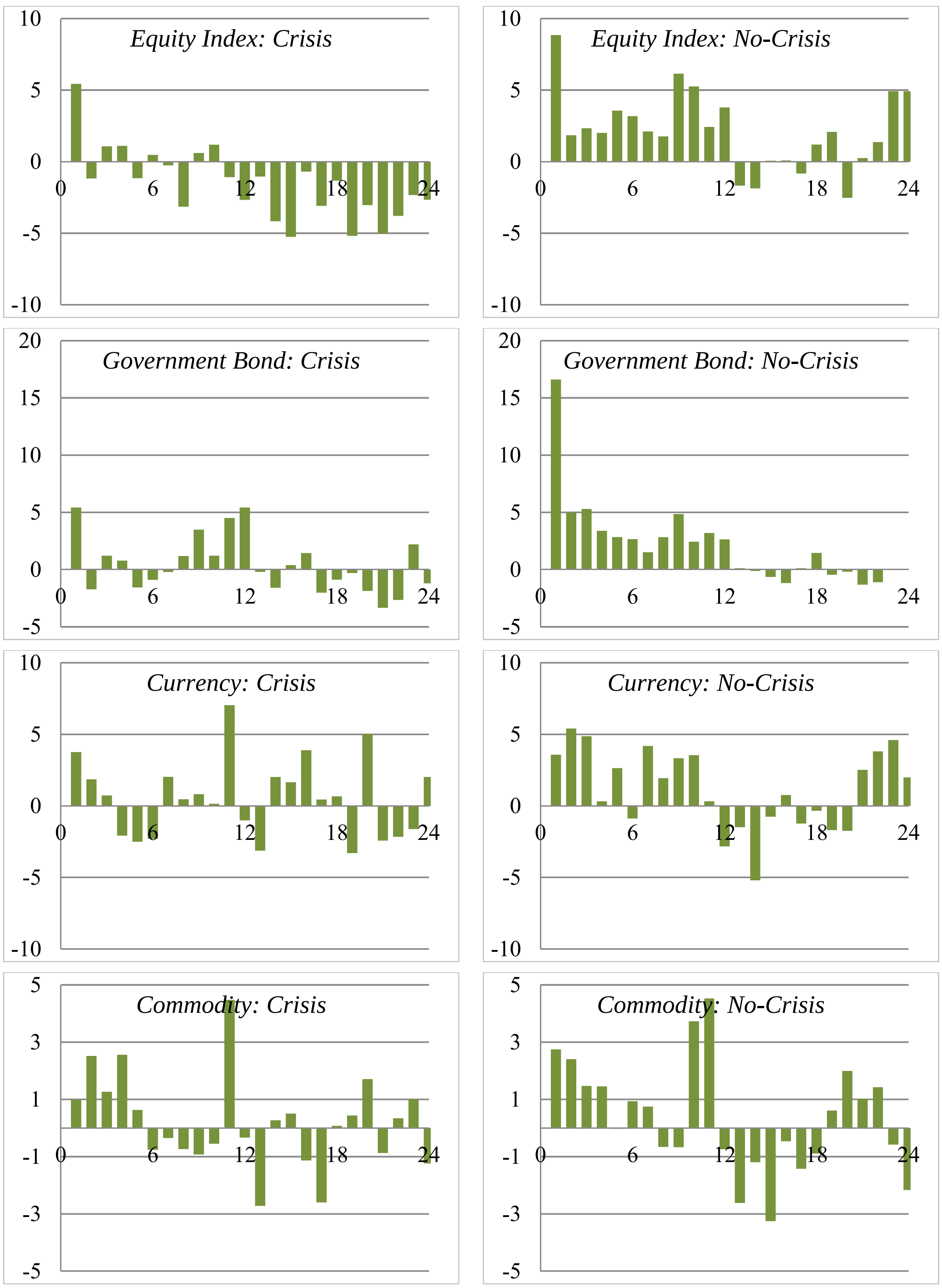


Figure 3.10
Time Series Correlation by Asset Class: Test Statistic

Monthly excess returns of each instrument are regressed on lagged excess returns over a range of time horizons. The sample consists of data from 1921 to 2013 and the regression model is $er_t^i/\sigma_{t-1}^i = \alpha + \beta_1 er_{t-l-1}^i/\sigma_{t-l-1}^i + \varepsilon_t^i$. The sample is divided by asset class and then between crisis and no-crisis market periods, with crises periods are assumed to last two years from the start date. The test-statistic for β_1 for each lag from one to twenty-four months is reported for each asset class for crisis and no-crisis periods.



3.B.2 The Commodity Anomaly and the Inter-temporal Asset Pricing Model

An examination of the results presented in Table 3.6 shows that for the diversified, equity index, government bond and currency portfolios the performance is better in no-crisis periods than crisis periods. These results are consistent over different definitions of crises and across different sample periods. The performance of the commodities portfolio stands out, being higher in periods of crisis[21]. It is also the only portfolio that shows a noticeable difference in volatility between crisis and no-crises periods, being about 50% higher in crisis periods, while the difference is less than 10% for all other asset classes. The anomaly reflects previous evidence that suggests the performance characteristics of commodity investments differ from other asset classes, (see, for example, Erb and Harvey (2006), Gorton and Rouwenhorst (2006) and, more recently, Schneeweis *et al.* (2008)).

The asynchrony between the cycles of commodities and other assets is compatible with the inter-temporal asset pricing model (ICAPM) of Merton (1973). The model focuses on investors maximising lifetime consumption given variable investment opportunities. The ICAPM produced by Merton is a theoretical framework, subsequently a number of authors have provided interpretations of the model which allow for tractable and intuitive analysis of its implications for financial markets. These interpretations can provide mechanisms to explain the asynchrony. In general, the different the mechanisms, a selection are discussed in detail below, rely on changes in the relative preference of investors between consumption and investment. These changes, by associating commodities with consumption and financial assets with investment, allow the prices of these two asset classes to diverge when there is a change in economic state.

An early interpretation, the consumption capital asset pricing model (Breeden (1979)) defines an asset's exposure to consumption rather than market returns as the source of returns above the risk free rate. Using this model is can be shown that there is an inverse relationship between consumption and expected investment returns.

Hall (1988) analyses the ICAPM to demonstrate an inter-temporal substitution between saving (financial assets) and consumption (commodities). Investors respond to a change in economic state by substitution financial assets for consumption, resulting in diverging

[21] A similar pattern is identified in the analyses of time series momentum across varying economic states (Section 4.4) and economic uncertainty (Section 4.7).

return series. The relative attractiveness of financial assets to investors are represented by a changing discount rate by Grossman and Shiller (1981) and later Campbell and Vuolteenaho (2004). Analysis by Maio (2005) focuses on risk aversion and demonstrates that the model implies a counter cyclical risk aversion.

Fama (1996) uses a different approach to produce similar results when he reinterprets the ICAPM in a mean-variance efficient framework. Investors divide their wealth between current consumption and investment. A change in state of the economy alters the relative utility of the financial and consumption assets to investors, resulting in different return characteristic.

It should emphasised that while the ICAPM in its various interpretations provides reasons to expect differences between the return structure of commodities and financial assets around changes market states, it is not possible to extend the model to predict the details of the differences in the performance of time series momentum demonstrated here. Although the ICAPM can be regarded as a superior model of reality to the CAPM, its complexities, along with the underlying assumptions, make it difficult to interpret (Fama (1996)). Neither the time varying risk of Maio (2005) or the discount rate model of Campbell and Vuolteenaho (2004) improve on the three factor Fama-French model in explaining equity returns while, in a more limited scenario, Jagannathan (1985) highlights the difficulty of extending the model to understand the of price commodities.

Despite this, the evidence of negative correlation between the performance profiles of a commodity portfolio and the financial portfolios in a crisis is important. It indicates that commodities can reduce the overall exposure of a multi-asset-class time series momentum portfolio to economic risk and as such argues for a higher relative weight for commodities in such a portfolio.

Chapter Four

Time Series Momentum and Macroeconomic Risk

Abstract[22]

The time series momentum strategy has been shown to deliver consistent profitability over a long time horizon. Funds pursuing these strategies are now a component of many institutional portfolios, due to the expectation of positive returns in equity bear markets. However, the return drivers of the strategy and its performance in other economic conditions are less well understood. The authors find evidence that the returns to the strategy are connected to the business cycle. Returns are positive in both recessions and expansions, but profitability is especially high in expansions. About 40% of returns are due to time varying factor-related risk exposure, consistent with rational asset pricing theories having a role in explaining the profitability of the strategy.

[22] This paper is currently in revision for resubmission to the *Financial Analysts' Journal*. The research reported in this paper has been presented at the following conferences; FMA Europe, Venice, FMA International, Orlando, and as part of the Financial Seminar Series at Queen's University, Belfast, all 2015 and INFINITI 2017 in Valencia. Lead author, John O'Brien, co-author, Mark Hutchinson.

4. Time Series Momentum and Macroeconomic Risk

4.1 Introduction

Subsequent to strong performance in the 2008 financial crisis Commodity Trading Advisors (CTAs) pursuing time series momentum strategies have experienced large inflows and are now a feature of many institutional investor portfolios.[23] For many investors the intuition behind including CTAs in their portfolio is primarily the expectation of high performance during equity bear markets.[24]

Though choosing a strategy due to an expectation of positive performance during these periods is reasonable, it disregards the drivers of profitability of the strategy and may convey the idea that high returns are exclusive to equity bear markets. Unlike traditional asset classes or other hedge fund strategies, there is scant academic evidence to date on the interaction between the returns of time series momentum and the business cycle. While the academic literature does show that the strategy has historically generated consistently positive returns, and that at least a portion of time series momentum returns are due to behavioural factors, it is a common sentiment amongst investors that performance is equity market period specific.

In our paper, to help investors understand the drivers of profitability, we explicitly test the connection between time series momentum strategies and the business cycle. We arrive at four key findings. First, time series momentum portfolio returns exhibit statistically significant differences across the business cycle. While positive in both, typically the performance of the portfolio is higher in economic expansions than recessions. Second, we show that though a linear macroeconomic factor model has little explanatory power, a model which allows the coefficients to vary through time, does result in several of the macroeconomic factors having a statistically significant relationship with time series momentum. Third, we show that when time series momentum portfolios are formed on either the factor-related or asset-specific portions of financial futures returns they generate statistically significant excess returns in both cases, with about 40 percent of returns coming from the factor-related portion. Finally,

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[23] According to data from Barclay hedge as of the 3rd Quarter of 2014 CTA assets under management (AUM) was $312.6 billion.

[24] See, for example, "Global worries forecast to boost flow of assets", Financial Times, June 9th 2012.

using a new estimation approach, we find that time series momentum generates higher returns in periods when economic uncertainty is lower.

From a practitioner's perspective, these results show that there is a role for rational asset pricing in explaining at least a portion of the returns to time series momentum; the strategy is related to macroeconomic risk factors which have previously been shown to be important in explaining the returns of both traditional and hedge fund portfolios; and perhaps most importantly, our evidence points to how practitioners can expect performance to vary across different future macroeconomic environments. In the next section we review the related literature and discuss how our results link to and extend this literature.

4.2 Literature Review

The literature on time series momentum is typically focused on the performance of different variations of these strategies for particular markets in specific periods (see for example Erb and Harvey (2006), Miffre and Rallis (2007) and Fuertes *et al.* (2010) for commodities, and Okunev and White (2003) and Menkhoff *et al.* (2012b) for currencies). The evidence of these studies is generally positive on the performance of time series momentum with positive Sharpe ratios and little correlation with traditional asset classes. Our paper compliments Moskowitz *et al.* (2012) who introduce multi asset class time series momentum to the literature. In a comprehensive study Moskowitz *et al.* (2012) investigate how time series momentum relates to market movements, sentiment, and the positions of speculators; finding evidence supporting a behavioural explanation for time series momentum profitability. Our study builds upon Moskowitz *et al.* (2012) in that we focus on macroeconomic factors which have been shown to be important for hedge funds and traditional portfolios, employ methodologies which directly incorporate time variation in factor exposures, and provide evidence that rational asset pricing may also be important in explaining returns.

Recent evidence linking time series momentum and the broader macroeconomy (Hutchinson and O'Brien (2014)) shows that following each of the six largest financial crises in the last hundred years, there was an extended period where time series momentum performance was below average. Though Hutchinson and O'Brien (2014) suggest several explanations why the performance of the strategy might differ in different economic conditions, unlike our study, they provide no empirical evidence connecting the strategy to the business cycle. The present paper also addresses a gap in Hutchinson and O'Brien (2014) by identifying the link between the business cycle and their finding that time series momentum tends to perform below average following periods of financial crisis. Using a new methodology, we document that uncertainty around changes in macroeconomic factors is the transmission mechanism linking the below average returns following large global financial crises and the business cycle.

By finding a link between the macroeconomy and time series momentum in a time varying framework we build upon several related papers on time series and cross-sectional momentum.[25] The cross-sectional momentum literature finds a strong relationship between macroeconomic factors and returns (Chordia and Shivakumar (2002)). While, to date, no one has considered this specification for time series momentum, related literature has demonstrated the lack of explanatory power for a range of traditional factors in a linear framework (Menkhoff *et al.* (2012b) and Moskowitz *et al.* (2012)).[26] We find that the relationship between returns and macroeconomic factors is only revealed in a model which explicitly allows for time varying exposure to risk factors. However, our conditional model results show that a significant portion of time series momentum returns are not explained by the macroeconomic factors.

Within the cross-sectional momentum literature Conrad and Kaul (1998) argue that profitability is due to differences in cross-sectional expected returns. Illustrating this, Chordia and Shivakumar (2002) demonstrate that when the returns of the underlying equities into are divided into macroeconomic factor-related and asset-specific components, the majority of cross-sectional momentum profitability comes from the portion of equity returns explained by macroeconomic factors. Contrary to this, in the first study to consider the returns of time series momentum from this perspective, we find that the returns to our portfolios are attributable to both the asset-specific and factor-related components of financial futures.

[25] As noted by Moskowitz *et al.* (2012) cross-sectional momentum and time series momentum are related but different strategies. The key difference being that cross-sectional momentum trading decisions are based upon the historical return of a security relative to other securities, whereas time series momentum is based upon the historical return of a security, considered independent of other securities. See Goyal and Jegadeesh (2015) for a decomposition of both strategies.
[26] We acknowledge that the broad range of drivers of returns investigated by Moskowitz *et al.* (2012) do relate to time variation in strategy performance.

More recently, the hedge fund literature has linked the performance of a range of hedge fund strategies to economic uncertainty. Bali *et al.* (2014) find that the sensitivity of hedge funds to uncertainty about the economy is important in explaining the cross-sectional deviation in their performance. In the first study to apply this methodological approach to time series momentum, our evidence suggests that time series momentum returns tend to be higher when economic uncertainty is lower than average.

4.3 Data and Methods

In this section we describe the selection of the sample period and the data used in the analysis. The dataset consists of individual exchange traded futures contracts, synthetic forward contracts and a range of macroeconomic variables.

4.3.1 Futures Data

In this paper we investigate the relationship between macroeconomic variables and the returns of the time series momentum investment strategy. As consistent monthly macroeconomic data only becomes available from the late 1940s, we specify January 1950 as the starting point for the analyses.[27] The sample period runs to the end of September, 2014. We split the sample into two sub-periods, January 1950 to December 1979 and January 1980 to September 2014, based around the peak of the great inflation. The first period is characterized by high inflation and increasing interest rates, whereas from 1980 inflation fell quickly and remained in a range of 2% to 5% for most of that period.[28] In this second sub-period interest rates fell steadily, from a high of 15.5% in 1981 to a low of 1.7% in 2012.[29] Dividing the sample into these two sub-periods allows us to assess performance in different long term interest rate cycles.

The futures data set consists of twenty one commodities, thirteen government bonds, twenty one equity indices and currency crosses derived from nine underlying rates covering the period from January 1949 to September 2014. The data consists of a combination of exchange traded futures data and forward prices derived from historical data. The momentum signals and portfolio returns are based on continuous return series. Using only exchange traded futures contracts would limit the time frame of the study to post-1980. In order to extend the study period backwards we follow the methodology

[27] We also use data for the twelve months prior to January 1950 to generate trading signals for the initial time series momentum portfolios.
[28] Annual change in US CPI, source Federal Reserve Economic Database.
[29] US Treasury 10 Year yield, source Federal Reserve Economic Database.

used in other long term studies of time series momentum (see, for example, Hurst *et al.* (2012)) and combine exchange traded prices with synthetic forwards created from the underlying instruments. Exchange traded futures' prices are available from Datastream from 1980 to the present. Prior to this period, we obtain continuous return series for commodity futures from Commodity Systems Inc. and MSCI currency data from Datastream. All older data is sourced from Global Financial Data. Table 4.1 shows a full list of the futures used in the study and data sources are discussed in greater detail in Appendix 4.A.

Where a futures contract trades on an exchange, the return series of the individual futures contracts are combined to produce a continuous excess return series. Where futures contracts are not available, forward prices are created by combining the underlying spot price, yield and risk free rate. These two approaches are discussed below.

4.3.1.1 Continuous Returns from Futures Contracts

Continuous return series are created from futures where daily price and volume data is available. We calculate the daily excess return of the most liquid contract. This is generally the front month or the next-nearest to delivery month. We select the most liquid contract as follows. At time, *t*, the average volume over the previous three trading days is measured for each of the live delivery dates. We select the contract with the highest volume to be recorded as the excess return for that day. To replicate the practicalities of rolling contracts, once we select a further delivery month, we do not allow the excess return of nearer delivery months to be selected again.

4.3.1.2 Continuous Return Forward Prices

Where exchange traded futures are not available, excess return series are created from the underlying spot price, risk free rate and yield. The excess return from buying a forward at the start of a month and holding it to month end, er_1, is given by:

$$er_1 = (1 + r_1)\left(\frac{1+q}{1+r_f}\right)^{(1/12)} - 1 \tag{4.1}$$

where r_1 is the spot price return for the month, r_f is the one month risk free rate, and q is the annualized yield. In order to confirm the validity of using synthetic forwards, a number of tests were carried out where exchange traded futures returns were replaced by synthetic forward returns. The series were typically almost perfectly correlated and in all cases results were close to identical.

Table 4.1
Future Contracts

The table provides a list of the underlying futures contracts used to create the time series momentum portfolios used in this study. Each future is listed with its average annual excess return, volatility and the date the return series becomes available. The futures are divided into four classes; Commodities, Government Bonds, Equity Indices and currencies. All data series end in September 2014.

	Start Date	Annual Return	Annual Vol.		Start Date	Annual Return	Annual Vol.
Commodity Futures				*Equity Index Futures*			
COCOA	Jan-66	-0.48	28.56	SPI 200-Australia	Jan-50	3.78	17.01
COFFEE	Sep-72	-1.47	37.87	S&P TSX60-Canada	Jan-70	3.19	16.42
COPPER	Jan-66	4.23	27.51	Dow Jones-US	Oct-77	4.12	15.28
CORN	Aug-50	-3.24	22.26	NASDAQ 100-US	Apr-96	8.18	27.29
COTTON	Apr-67	-0.83	25.39	AEX-Netherlands	Jan-70	5.02	18.91
GAS OIL	Sep-03	9.78	28.87	CAC 40-France	Jan-70	3.36	20.26
GOLD	Feb-75	3.97	19.97	DAX-Germany	Jan-50	5.82	18.50
LEAN HOGS	Mar-66	2.94	26.05	MDAX-Germany	Mar-05	11.14	21.36
LIGHT CRUDE	Mar-83	6.14	33.96	HANG SENG-Hong Kong	Jan-70	10.53	33.29
LIVE CATTLE	Dec-64	4.31	16.91	S&P Midcap-US	Feb-92	8.19	16.78
NATURAL GAS	Apr-90	-10.76	56.64	NIKKIE 225-Japan	Jan-50	6.08	20.30
NY HEATING OIL	Jan-80	6.12	31.97	S&P 500–US	Jan-50	5.48	14.52
PALLADIUM	Feb-77	5.75	35.08	KOSPI 200-Korea	Jan-65	8.86	27.38
PLATINUM	Feb-64	2.99	26.91	FTSE 100-UK	Jan-50	5.05	17.90
RBOB GASOLINE	Oct-05	6.20	32.28	IBEX 35-Spain	Jan-70	1.68	20.85
SILVER	Jul-73	-0.51	31.00	MIB-Italy	Jan-50	2.11	21.95
SOYABEAN MEAL	Sep-51	3.57	28.69	Russell 2000-US	Aug-07	6.09	21.91
SOYABEAN OIL	Aug-50	6.84	27.79	OMXS 30-Sweden	Jan-70	6.77	21.93
SOYABEANS	Aug-50	3.31	24.02	SMI-Switzerland	Jan-70	5.39	16.45
SUGAR	Jan-66	-2.99	40.52	SMI Midcap-Switzerland	Sep-05	6.17	17.47
WHEAT	Aug-50	-4.09	23.14				
Bond Futures				*Currency Forwards*			
Australia-10Y	Jan-50	0.50	6.73	AUD/USD	Aug-71	-1.69	11.51
Australia-3Y	May-88	4.03	9.47	CAD/USD	Aug-71	-0.39	6.54
Canada-10Y	Jan-50	1.29	6.22	CHF/USD	Aug-71	-0.80	12.23
US-5Y	Jan-50	0.82	4.98	EUR/USD*	Aug-71	0.11	10.91
US-2Y	Jun-90	1.62	1.68	GBP/USD	Aug-71	-0.77	10.15
US-10Y	Jan-50	1.21	6.75	JPY/USD	Aug-71	-0.14	11.18
US-30Y	Jan-50	0.78	9.77	NOK/USD	Aug-71	-1.36	10.58
Germany-5Y	Oct-91	2.97	3.22	NZD/USD	Aug-71	-1.97	12.41
Germany-30Y	Sep-05	5.34	11.88	SEK/USD	Aug-71	0.05	11.03
Germany-2Y	Mar-97	0.92	1.32				
Germany-10Y	Jan-50	2.33	5.05				
Japan-10Y	Jan-50	2.67	6.15				
UK-10Y	Jan-50	1.21	8.27				

* DEM/USD prior to the introduction of the Euro in Jan 1999

4.3.2 Economic Data

Recent evidence has documented a strong link between macroeconomic risk and hedge fund strategies (Bali *et al.* (2014)). Due to the power of these factors for hedge funds we specify the economic factors presented in Bali *et al.* (2014) for all analyses.[30] Consistent with Bali *et al.* (2014) we use the Federal Reserve Economic Database, the Bureau of Labor Statistics and the online data libraries of Robert Shiller and Kenneth French for economic data. A more detailed description of the sources can be found in Appendix 4.A. Information is available for all eight factors from January 1950 to September 2014. We also examine the performance of time series momentum portfolios in periods of economic expansion and recession, based on definitions from the National Bureau of Economic Research (NBER) and GDP data from the Federal Reserve.

4.3.3 Time Series Momentum Portfolio

The analyses of time series momentum in this paper are based on time series representing the performance of the strategy across four distinct asset class sub-portfolios and a diversified portfolio combining the four sub-portfolios.

The portfolios and their associated return series are created from the excess returns of the instruments in the data universe. Where possible, excess returns are taken directly from futures contracts trading on public exchanges, with the return of the most active contract, defined as a function of trade volume, used as the excess return. Where futures exchange data is not available for earlier periods, synthetic forward prices are created by combining the underlying spot price, yield and risk free rate.

In creating the time series of time series momentum portfolios we use a twelve month formation (look-back) period and a one month holding period.[31] These are the most common definitions used in the literature (see, for example, Hurst *et al.* (2012), Moskowitz *et al.* (2012) and Baltas and Kosowski (2013)). The first step is to assign each instrument a momentum signal, defined as

$$M_{t,k}^{i} = sign\left(\sum_{1}^{k} \log\left(1 + r_{t-k}^{i}\right)\right) \tag{4.2}$$

Where, $M_{t,k}^{i}$ is the momentum of instrument *i* at time *t* formed with a look back period of *k* months and r_{t-k}^{i} is the excess return of instrument *i* at time *t* - *k*.

[30] For robustness we also conducted all analyses using Chordia and Shivakumar (2002) and Chen *et al.* (1986) factors. The results (unreported) for all analyses, with the exception of economic uncertainty, were stronger with these alternative specifications.

[31] Repeating the analyses using a range of different parameters, including the momentum signal defined in Hutchinson and O'Brien (2014), produces very similar results.

The instruments are divided into four asset classes, Equity Indices, Government Bonds, Foreign Exchange and Commodities and a time series momentum portfolio is created for each class. Each instrument is given a weight proportional to its momentum signal and inversely proportional to its volatility, so the size of the position is

$$w_t^i = \frac{1}{N_c} M_t^i . \frac{V_o}{\sigma_t^i} \tag{4.3}$$

Where w_t^i is the weight of instrument i held in the portfolio at time t and σ_t^i is the corresponding volatility. N_c is the number of instruments in the asset class. This adjusts the weights so that each sub-portfolio is allocated the same level of risk irrespective of the number of assets in the class.[32] The position is scaled by V_o, the choice of this is arbitrary, but is set at 40% so the resulting return series have volatility levels in a range from 10% to 15%, equivalent to those reported in the literature, allowing easier comparison (Moskowitz *et al.* (2012)). The portfolio is rebalanced monthly[33] so the return series for each sub-portfolio is

$$r_t^c = \sum_{i=1}^{N_c} \left(r_t^i . w_t^i \right) \tag{4.4}$$

Where r_t^c is the excess return of sub-portfolio c in time period t. The time series for the diversified portfolio is the sum of the return series of the four sub-portfolios.[34]

4.3.3.1 Ex-ante Volatility

We replicate the methodology of Moskowitz *et al.* (2012) to create the ex-ante volatility estimates. This method uses an exponentially weighted squared daily returns model to estimate volatility, a model similar to a univariate GARCH model. The annualized volatility for each instrument is calculated as:

$$\sigma_t = \sqrt{261 \sum_{i=0}^{\infty} (1-\delta)\delta^i (r_{t-1-i} - \overline{r_t})^2} \tag{4.5}$$

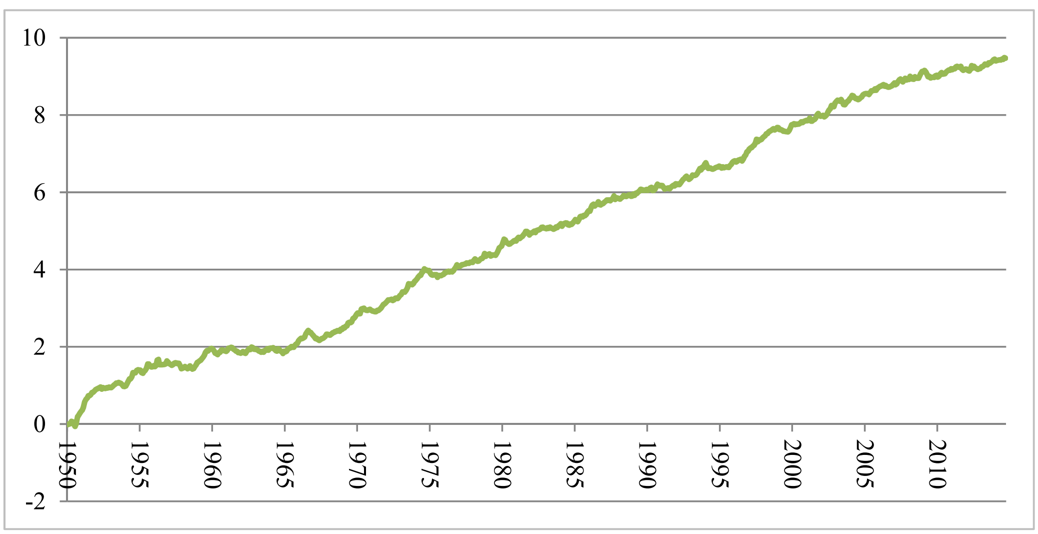
[32] Risk levels are not exactly matched as we do not include correlation between assets.
[33] The portfolio construction does not allow for intra-month changes in volatility.
[34] In periods where there are fewer than four portfolios, returns are scaled so the diversified portfolio has constant target volatility throughout the entire sample period.

The parameter δ is chosen so that the center of mass of the weights is 60 days, so data from the last sixty days carries equal weight to all data up to then. The same model is used for all instruments.

Transaction costs are included in the performance measures in this paper, using the cost model described by Hurst *et al.* (2012), where costs are a function of asset class and time. All returns presented are in excess of the risk free rate. In general results are presented for three time periods: the entire sample period, January 1950 to September 2014; and two sub-periods, January 1950 to December 1979 and January 1980 to September 2014.[35]

The cumulative excess return of the diversified portfolio is shown in Figure 5.1 and the summary performance statistics for the diversified portfolio and the four asset class sub-portfolios are presented in Table 4.2.

Figure 4.1
Performance of the Diversified Time Series Momentum Portfolio
The figure shows the natural logarithm of the cumulative excess return series of a diversified time series momentum portfolio from January 1950 to September 2014. Excess returns are presented net of transaction costs and gross of fees.



The most striking feature is the consistent excess returns generated by the time series momentum strategy in the long run. The diversified portfolio and all sub-portfolios are positive over the full period and both sub-periods. Over the full sample the diversified

[35] FX results do not begin until August 1972, so results reported for this asset class in the earlier sub-period are based on a relatively short sample period.

portfolio generates a mean annualized excess return of 15.75% with a volatility of 12.55% which translates into a Sharpe ratio of 1.25.

Table 4.2
Performance of Time Series Momentum Portfolios

The table reports the average annualised excess return and volatility of five time series momentum portfolios, comprising of a diversified portfolio and four asset class sub-portfolios; equity indices (Equity), government bonds (Bonds), currencies (FX) and commodities (Commodity). The results are presented from January 1950 to September 2014 and over two sub-periods, January 1950 to December 1979 and January 1980 to September 2014. The FX and Commodity time series begin in August 1972 and August 1951, respectively. All other series begin in January 1950. Excess returns are presented net of transaction costs and gross of fees.

		Diversified	**Equity**	**Bonds**	**FX**	**Commodity**
1950-2014	Return (%)	15.75	5.18	5.29	1.81	2.04
	Vol. (%)	12.55	5.41	6.39	4.45	4.17
1950-1979	Return (%)	16.60	5.03	5.46	2.46	1.55
	Vol. (%)	13.01	4.97	6.26	5.91	5.00
1980-2014	Return	15.03	5.30	5.15	1.67	2.45
	Vol. (%)	12.14	5.77	6.50	4.08	3.34

The pattern of strong positive returns is consistent with studies of time series momentum strategies by Moskowitz *et al.* (2012) for the period 1985 to 2009 and Hurst *et al.* (2012) who examine an extended period from 1903 to 2012. It is also notable that there is little difference in performance for the diversified portfolio or the Bond sub-portfolio between the two sub-periods, despite the dramatically different interest rate regimes.

4.4 Time Series Momentum across the Economic Cycle

To examine the performance of time series momentum across the economic cycle, we initially measure and compare the performance of time series momentum in different economic states. The states are defined as a function of an economic or interest rate spread variable. Each month's return is assigned to one of the two possible states. The average performance of the strategy in each state is calculated as the annualized mean of the pooled excess returns for that state.

The variation in performance of time series momentum under different economic and interest rate spread states is analysed here, first for the business cycle using two different definitions of recession, and then by using interest rate spreads (term and default) to define the state.

4.4.1 Economic States

The variation in performance of time series momentum under different economic conditions is tested by splitting the return of the time series momentum return series according to the contemporaneous economic state. The economy is allowed to be in one of two states, expanding or contracting. Two definitions of economic state are used. The first uses NBER recession definitions to define the state of the economy as contracting, with all other periods defined as expanding. The second uses the sign of the change in GDP to define the economic state; a positive change corresponded with an expansion and a negative change with a recession.[36] The results are displayed in Table 4.3.

Using either definition, the economy expands in approximately 85% of months and contracts in 15% of months, a pattern repeated in both sub-periods. Irrespective of the definition the results of the analysis are consistent. The diversified, equity, bond and FX portfolios generate higher returns in periods of expansion than recession. This is seen over both the full sample and, in general, across the sub-periods.[37] Over the full period the average performance in expansions exceeds that in recessions by a statistically significant 8.5% (NBER) and 7.6% (GDP).

Consistent with the results of Hutchinson and O'Brien (2014) the commodity portfolio provides an exception to this pattern, performing better in recessions than expansions, returning 3.58% in recessions against 1.86% in expansions (NBER definition). This result highlights the diversification benefits of commodities in a time series momentum portfolio.

4.4.2 Spread States

In order to further explore the relationship between economic conditions and the performance of times series momentum we define economic conditions using two key interest rate spreads. These proxy for short term (term spread) and long term (default spread) peaks and troughs in the business cycles (Fama and French (1989)). The term spread is defined as the difference between the 10 year and three month US treasury rate

[36] There is overlap between four of the ten NBER recessions analysed here and four of the five post-1950 global financial crises twenty four month periods examined in Hutchinson and O'Brien (2014), though the NBER recessions are much shorter (average peak to trough length of 11.1 months).

[37] In the first sub-period bond time series momentum returns are marginally greater in expansion periods using the NBER measure (5.60% compared to 5.05%), while they are marginally smaller using the GDP measure (5.51% against 5.57%).

and the default spread is the difference between the BAA and AAA rated US corporate bonds.

Table 4.3
The Performance of the Time Series Momentum through the Economic Cycle

The table presents the average annualised excess return of the time series momentum strategies in periods of economic expansion (Exp.) and recession (Rec.). Panel A presents the results based on the NBER definition of economic cycles, while Panel B presents results based on changes in GDP. The first row of each panel (% Time) displays the proportion of the sample period that the economy was in expansion or recession. Results are presented for a diversified portfolio and four asset-specific sub-portfolios; equity indices, government bonds, FX and commodities. The results are presented from January 1950 to September 2014 and over two sub-periods, January 1950 to December 1979 and January 1980 to September 2014. The FX and commodity time series begin in August 1972 and August 1951, respectively. All other series begin in January 1950. Excess returns are presented net of transaction costs and gross of fees. Statistically significant differences, calculated using a one tailed test, are indicated at confidence levels of 10% (*), 5% (**) and 1% (***).

	1950-1979		1980-2014			1950-2014		
	Exp.	Rec.	Exp.	Rec.		Exp.	Rec.	
Panel A: NBER Economic Cycles								
% Time	84.72	15.28	86.57	13.43		85.71	14.29	
Equity	5.53	2.31	5.84	2.17		5.70	2.24	*
Bonds	5.60	5.05	5.75	2.02		5.68	3.52	
FX	4.01	-3.80	2.39	-2.43	***	2.66	-2.74	***
Commodity	1.47	2.68	2.17	4.47		1.86	3.58	
Diversified	17.37	10.25	16.14	6.22	*	16.71	8.22	**
Panel B: GDP Data								
% Time	84.17	15.83	87.77	12.23		86.10	13.90	
Equity	5.54	2.37	5.67	3.00		5.61	2.67	*
Bonds	5.51	5.57	5.99	-0.06	**	5.77	2.91	
FX	3.67	-2.67	2.11	-0.86	*	2.37	-1.27	**
Commodity	1.48	2.57	2.32	3.59		1.95	3.05	
Diversified	17.10	11.93	16.08	5.67	*	16.55	8.97	**

In the following analyses, a month is defined as High (Low) if the value of the variable in that month is higher (lower) than the mean for the sample period.[38] The results are displayed in Table 4.4.

The diversified portfolio performs better in periods where the term spread is low, at business cycle peaks. It generates a return of 18.76% in the low term spread state compared to 11.95% in the high state over the full period, a statistically significant difference of 6.8%. It also performs better in the low state relative to the high state in

[38] The definition of months as high (low) in a sub period is defined relative to the mean value for that sub-period. This can lead to months being defined differently depending on the sample period mean.

both sub-periods. In general the sub-portfolios also outperform in the low term spread state over the full period and both sub-periods.[39]

Table 4.4
The Performance of Time Series Momentum in Short Term and Long Term Business Cycle Expansions and Contractions

The table presents the average annualised excess return of the time series momentum strategies at different stages of the market cycle, based on interest rate spreads. In each case, a month is defined as high (low) if the value of the spread for that month is greater (less) than the average value for the sample period. The average return for high (low) periods is the annualized mean of the excess return in all high (low) spread periods. Panel A presents the results based on the term spread of interest rates (US 10Y T-Bond Yield – 3M US T-Bill Yield). Panel B presents the results based on the default spread of interests rates (US BAA Corporate Bond Yield – US AAA Corporate Bond Yield). The first row of each panel (% Time) displays the proportion of the sample period that the spread was above (below) the average for the period. Results are presented for a diversified portfolio and four asset class sub-portfolios; equity indices, government bonds, FX and commodities. The results are presented from January 1950 to June 2013 and over two sub-periods, January 1950 to December 1979 and January 1980 to September 2014. The FX and commodity time series begin in August 1972 and August 1951, respectively. All other series begin in January 1950. Excess returns are presented net of transaction costs and gross of fees. Statistically significant differences, calculated using a one tailed test, are indicated at confidence levels of 10% (*), 5% (**) and 1% (***).

	1950-1979			**1980-2014**			**1950-2014**		
	High	**Low**		**High**	**Low**		**High**	**Low**	
Panel A: Term Spread									
% Time	47.78	52.22		53.00	47.00		48.01	51.99	
Equity	5.60	4.53		4.57	6.22		4.28	6.05	*
Bonds	3.03	7.79	***	4.82	5.72		4.27	6.39	*
FX	2.22	3.07		0.27	3.41	***	0.86	3.15	
Commodity	1.22	2.09		1.93	3.09		2.36	1.87	
Diversified	13.33	18.98		11.59	18.44	**	11.95	18.76	***
Panel B: Default Spread									
% Time	34.17	65.83		42.69	57.31		45.56	54.44	
Equity	3.12	6.04	**	4.53	5.95		4.30	5.96	
Bonds	1.36	7.67	***	5.30	5.21		5.18	5.53	
FX	3.57	1.91		0.75	2.49		1.03	2.55	
Commodity	3.71	0.58	**	2.26	2.64		2.46	1.82	
Diversified	9.59	19.76	***	12.84	16.28		12.69	17.84	**

The pattern is repeated when looking at the default spread, where the time series momentum portfolios perform better in the low state, a proxy for expansions. Here the diversified portfolio generates a statistically significantly different return of 17.84% in the low spread state compared to 12.69% in the high state. Again, looking at the sub-

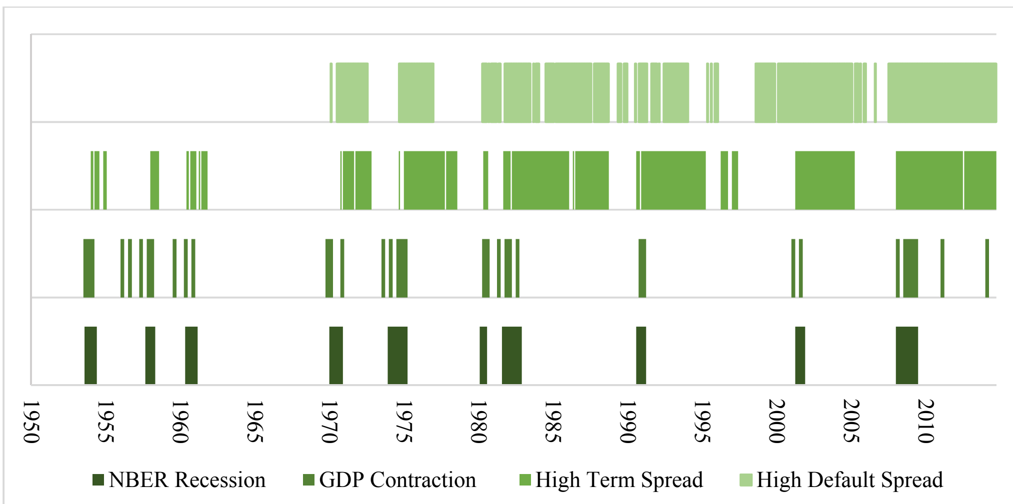
[39] There is one exception; in the 1950 to 1979 sub-sample period the equity portfolio marginally outperforms in the high term spread state.

portfolios and sub-periods, all typically perform better in the low default spread state compared to the high state.

4.4.3 Comparison of State Definitions

The previous analyses show that time series momentum underperforms when economies contract and interest rate spreads are high. These results are consistent over both the full period and each sub-period. This section compares the different state definitions, shown in Figure 4.2, and analyses the results from the previous two sections for consistency.

Figure 4.2
Indicators of Economic Conditions: January 1950 to September 2014
The figure economic state indicators use in analysis the performance of time series momentum; NBER business cycles, GDP growth, the term spread and the default spread. The periods associated with times series momentum are highlighted in each case.



There is significant overlap between the two measures of the economic cycle based on growth; the NBER recession definitions and change in GDP. The key differences are short periods of declining GDP, not sufficient to be defined as a recession and occasional months of GDP growth within recessions. It is reasonable to regard the GDP indictor as a timely, but noisy indicator of economic cycles defined by the NBER. There is little surprise in consistent results for the two definitions. The two interest rate spreads are also correlated with each other, having the same value 77% of the time between 1950 and 2014, again indicating similar results are to be expected.

Finally, it is necessary to compare the correlation of poor performance with periods of both high spreads and economic contraction. Work by Estrella and Hardouvelis (1991) and later by Estrella and Mishkin (1998) provides evidence that low term spreads precede recessions, demonstrated through a positive correlation between economic growth and lagged spread. This suggests that low term spread is associated with recession and consequently the results presented here are internally inconsistent.

An extension of the analysis by Wheelock and Wohar (2009) resolves the conflict. The authors confirm the positive relationship between lagged term spread. The relationship is also demonstrated in both the German and British economies strengthening the evidence. Importantly for the analysis here, the research also demonstrates that the sign of the correlation reverses when co-incident or leading values of term spread are used, again this is a consistent finding across three major economies. This associates recessions with high spreads. This relationship is also seen the state definitions used in this research with 73% of recession periods (NBER) coinciding with a high term spread. Consequently, times series momentum should be expected to have similar relative performance in these periods, consistent with the results presented in Sections 4.4.1 and 4.4.2.

It is an interesting aside to note that if low term spread can predict recessions, it may also be able to predict the poor performance of time series momentum associated with them.

4.5 Economic Factor Model Analysis

The Bali *et al.* (2014) model has eight economic and financial factors which have been shown to be particularly important for hedge funds. The factors are commonly used in literature, examples of which can be found in the models of Chen *et al.* (1986), Fama and French (1989) and Chordia and Shivakumar (2002).

The term structure (TERM) and default spread (DEF) are included in all three of the models listed above. Fama and French (1989) show that the variables track the long term and short term business cycles, respectively. The dividend yield (DIV) is associated with mean reversion in the stock markets and can also be interpreted as a proxy for time variation in risk premia (Chordia and Shivakumar (2002)). The change in GDP and the level of unemployment (UNEMP) capture current economic conditions. Short term interest rates (RREL) capture both expectations about future economic activity (Chordia and Shivakumar (2002)) and predict future equity market returns. Market returns (MKT) reflect changes in expectations of future growth.[40]The definitions of the eight factors are given in Table 4.5.

Table 4.5
Macroeconomic Risk Model Factor Definitions

The table presents the definitions of the eight economic factors that make up the economic model used in this study, based on the economic uncertainty model of Bali *et al.* (2014). The first column shows the factor name as used in Bali *et al.* (2014) and the second column defines the factor in terms of the underlying economic time series.

Factor	Definition
DEF	The default spread, the difference between BAA and AAA rated US corporate bonds
DIV	The aggregate dividend yield on the S&P 500
GDP	The monthly change in US GDP per capita
INF	Monthly inflation based on US CPI
MKT	The excess return on a value weight index of all US stocks (CRSP Universe)
RREL	The 3-month US T-Bill rate divided by its 12 month moving average
TERM	The term spread, the difference between 10 Year and 3 Month US Treasury rates
UNEMP	The total number unemployed divided by labour force.

The ability of the economic model to explain time series momentum returns is tested using two different sets of assumptions. First, that the relationship between the factors and the methodologies is constant through time, a linear factor (unconditional) model and then allowing the relationship to vary through time (conditional model).

4.5.1 Linear Factor Model

The linear factor model specifies economic factors as explanatory variables in the regression model

$$r_t^{tf} = \beta_0 + \sum_{n=1}^{N} \beta_n EF_t^n + \varepsilon_t \tag{4.6}$$

Where EF_t^n is the value of economic factor *n* at time *t*. N is the total number of explanatory variables (economic factors) and r_t^{tf} is the return of the time series momentum portfolio in time period *t*. The factor model is estimated for the full sample period and the two sub-periods. The ability of the factors to explain the returns of a time series momentum strategy is assessed based upon the magnitude and statistical significance of the respective regression co-efficient. A statistically significant

[40] To correct for long term trends in our extended sample period, the dividend yield factor (DIV) is measured relative to the lagged five year moving average and the short term rate (RREL) is calculated as a quotient rather than a difference.

regression coefficient is evidence of a relationship between the returns of time series momentum and economic conditions.

The results for the linear factor model are presented in Table 4.6. The table lists the factors and their corresponding *t*-statistics. Consistent with Moskowitz *et al.* (2012), the linear model provides little explanatory power for time series momentum at the portfolio or sub-portfolio level. Only four, of forty, coefficients are statistically significant. The market return factor (MKT) is significant for Equity and Bond portfolios and the short term rate (RREL) is significant for both the Equity and FX portfolios. At the diversified portfolio level, there is no statistically significant explanatory factor. The inability of a linear economic factor model to explain returns is reflected in the low values reported for the adjusted R^2 measure, which range from 0.12% to 1.40%.

4.5.2 Conditional Factor Model

The explanatory power of a conditional model can vary considerably from the unconditional (linear) specification (Griffin *et al.* (2003)), consequently we define a conditional test based on the methodology used in Chordia and Shivakumar (2002) and Griffin *et al.* (2003).

To allow for a time varying relationship between the time series momentum excess returns and the macroeconomic factors, at each month, we estimate, using the current month and prior 59 months, equation (7).[41]

$$r_t^{tf} = \beta_0 + \sum_{n=1}^{N} \beta_n EF_{t-1}^{n} + \varepsilon_t \qquad (4.7)$$

Where EF_t^n is the value of economic factor *n* at time *t*. *N* is the total number of explanatory variables (economic factors) and r_t^{tf} is the return of the time series momentum portfolio in time period *t*. We utilize a minimum of 60 months of data for our regressions and the t-statistics are based on Newey-West serial correlation consistent standard errors, since the rolling regressions are subject to autocorrelation in the estimates. If the economic factors fail to fully explain the returns from time series momentum, the intercept of the regression model will be positive and significant.

[41] We use a 60 month estimation period for the conditional model and portfolio study consistent with the cross-sectional momentum literature (Chordia and Shivakumar (2002)). In unreported analyses, we alternately use a 36 and 84 month estimation period. The results are very similar to those reported.

Table 4.6
Linear Regression Factor Model

The table presents the results of regressing the excess returns of five time series momentum portfolios; a diversified portfolio and four asset class sub-portfolios on the economic factor model. The table presents the regression coefficients and associated test statistics from the regression model $r_t^{tf} = \beta_0 + \beta_1 DEF_t + \beta_2 DIV_t + \beta_3 GDP_t + \beta_4 INF_t + \beta_5 MKT_t + \beta_6 RREL_t + \beta_7 TERM_t + \beta_8 UNEMP_t + \varepsilon_t$. Regressions are estimated from January 1950 to September 2014 for the diversified portfolio and the equity and bond sub-portfolios. The FX and commodity regressions are from August 1972 to September 2014 and August 1951 to September 2014, respectively. Coefficients significant at the 5% level are highlighted in bold. The adjusted R^2 are presented for each regression.

	INT	DEF	DIV	GDP	INF	MKT	RREL	TERM	UNEMP	Adj. R^2
Equity	**0.0070**	-0.0002	-0.0017	0.0009	-0.0017	**0.0003**	**0.0047**	0.0005	-0.0005	0.0140
	3.12	-0.12	-0.50	0.47	-1.01	**2.59**	**2.08**	0.81	-0.99	
Bond	0.0052	-0.0037	0.0030	0.0000	-0.0018	**-0.0004**	-0.0010	-0.0013	0.0010	0.0043
	1.94	-1.64	0.75	-0.02	-0.91	**-2.37**	-0.37	-1.69	1.49	
FX	0.0048	0.0008	0.0013	0.0031	-0.0032	0.0000	**0.0042**	-0.0003	-0.0004	0.0057
	1.80	0.46	0.40	1.29	-1.89	0.00	**1.96**	-0.43	-0.81	
Commodity	0.0025	0.0008	-0.0022	-0.0021	0.0036	-0.0001	-0.0005	0.0004	-0.0005	0.0049
	1.41	0.54	-0.80	-1.33	2.70	-0.61	-0.28	0.73	-1.14	
Diversified	**0.0218**	-0.0031	0.0041	0.0018	-0.0011	0.0000	0.0071	-0.0001	-0.0009	0.0012
	4.17	-0.71	0.52	0.40	-0.29	-0.01	1.35	-0.08	-0.75	

In Table 4.7 we report the results of estimating a conditional model which allows for time variation - the average coefficients from the rolling five year lagged regressions and their statistical significance. Unlike the unconditional model, six of the eight macroeconomic factors have statistically significant coefficients for the full sample. This evidence highlights that the conditional implementation of the model has some explanatory power for time series momentum returns. However, it is also noteworthy that the intercept for the model is positive and statistically significant in all three of the periods, consistent with time series momentum returns not being fully explained by the economic model. Later we investigate what portion of returns is attributable to macroeconomic risk exposure.

4.5.3 Time Series Momentum and Traditional Asset Classes

To highlight the time varying nature of the risk exposure of the time series momentum portfolios we show the return series of time series momentum, the relationship (beta) between these series and equity and bond markets in Figure 4.3. The excess total return of the S&P 500 Index is used to represent the equity market; while the excess total return of the 10 Year US Treasury Bond at constant maturity is used as a proxy for the bond market. Each graph displays three data series; the mean monthly return of the market factor over the prior sixty months, the mean monthly return of the time series momentum portfolio over the same period, and the beta of the time series momentum portfolio estimated relative to the relevant financial market, again over the prior sixty months.

Panel A shows the relationship between the diversified time series momentum portfolio and the equity market. Over the full period, the five year returns of the equity market are generally positive, and during this period the beta of the diversified portfolio is on average positive, reaching a maximum value of 0.75. The periods of negative beta, running approximately from 1970 to 1985 correspond to a poor period of performance for the equity market, where the return is lower than average and negative for a five year period around 1975. Two periods of negative beta occur after 2000 and coincide with falling equity markets in the periods following the collapse of the dotcom bubble and the failure of Lehman Brothers. Examining the relationship between the equity time series momentum portfolio and the equity market (Panel C) produces a very similar pattern; positive betas when equity markets are rising and negative betas when they are falling.

Table 4.7
Time Varying Regression Model

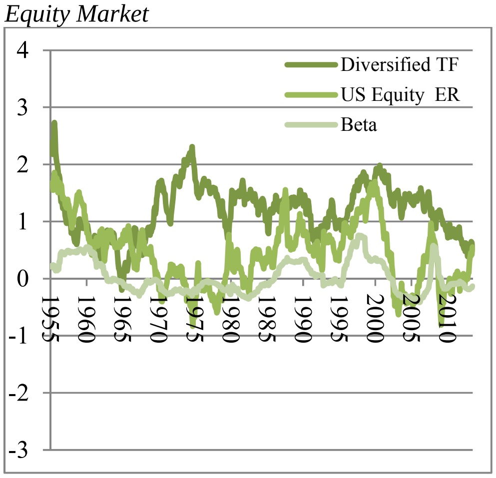
This table shows the average value of the time varying regression coefficients when the excess returns of a diversified time series momentum portfolio are regressed against the lagged economic model using $r_t^{tf} = \beta_0 + \beta_1 DEF_{t-1} + \beta_2 DIV_{t-1} + \beta_3 GDP_{t-1} + \beta_4 INF_{t-1} + \beta_5 MKT_{t-1} + \beta_6 RREL_{t-1} + \beta_7 TERM_{t-1} + \beta_8 UNEMP_{t-1} + \varepsilon_t$ over a sixty month window. The reported coefficient t-statistics are corrected for serial correlation in the error term using the Newey-West autocorrelation consistent errors. Significant coefficients (5% level) are shown in bold. Results are presented from January 1955 to September 2014 and for two sub-periods, January 1955 to December 1979 and January 1980 to September 2014.

	INT	DEF	DIV	GDP	INF	MKT	RREL	TERM	UNEMP	Adj. R^2
1955 - 2014	**0.0514**	**-0.0106**	**-0.0209**	**-0.0136**	**-0.0112**	-0.0001	0.0067	**0.0038**	**-0.0047**	0.0669
	8.86	-2.34	-2.50	-2.75	-2.75	-0.33	1.24	2.50	-3.55	
1955 - 1979	**0.0406**	**-0.0319**	**-0.0395**	-0.0083	-0.0067	0.0004	0.0206	0.0050	-0.0009	0.1221
	3.45	-3.18	-2.32	-1.21	-0.91	0.84	1.71	1.29	-0.34	
1980 - 2014	**0.0596**	0.0053	-0.0068	**-0.0176**	**-0.0146**	-0.0005	-0.0037	0.0030	**-0.0076**	0.0186
	7.76	0.94	-0.58	-2.14	-2.79	-1.28	-0.60	1.63	-4.82	

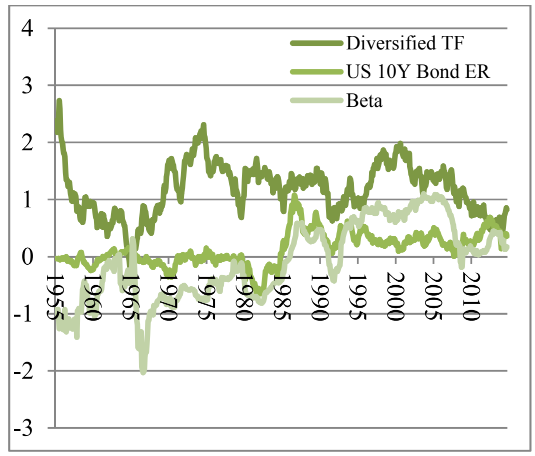
Figure 4.3
Rolling Beta of Time Series Momentum for Financial Markets

Each panel presents the average five year monthly total excess return of a time series momentum portfolio, the average five year monthly total excess return of an asset and the beta between the two. Panel A presents the returns of the US equity market and the diversified time series momentum portfolio. Panel B presents the returns of US Treasury bonds and the diversified time series momentum portfolio. Panel C presents the returns of the US equity market and the equity index time series momentum portfolio. Panel D presents the returns of US Treasury bonds and the government bond time series momentum portfolio. Results are presented from January 1955 to September 2014.

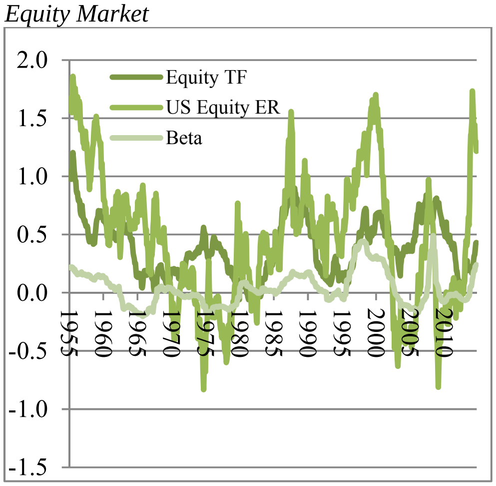
Panel A: Diversified Time Series Momentum & Equity Market



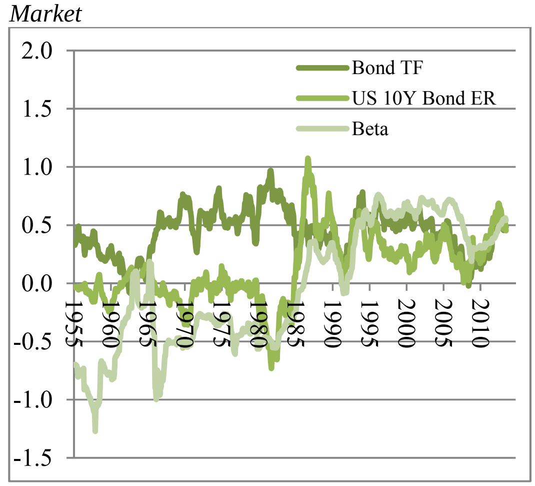
Panel B: Diversified Time Series Momentum & Bond Market



Panel C: Equity Time Series Momentum & Equity Market



Panel D: Bond Time Series Momentum & Bond Market



A similar analysis for the bond market is reported in Panel B and D. The excess return of the bond market can be divided into two distinct periods split by the peak of the great inflation in 1982. In the first period, bonds have a flat to small negative excess total return. Since then the excess returns of bonds have been consistently positive. Strikingly, the returns of the time series momentum portfolios are positive across all bond market conditions. In the early period, both the global and bond time series momentum portfolios have a significant negative relationship (beta) with the bond market excess return. In the later sub-period when bond returns are positive the portfolio beta is also positive. This provides evidence that time series momentum is profitable in rising and falling interest rate environments.

4.6 Momentum and Asset-Specific Returns

Returns to the cross-sectional momentum strategy have been shown to be primarily due to the component of individual equity returns explained by macroeconomic factors (Chordia and Shivakumar (2002)). This is important as it shows that the returns to cross-sectional momentum are in large part due to exposure to macroeconomic risk. In order to examine if this is also the case for time series momentum, we create two alternative time series momentum portfolios based on the decomposition of asset returns into a macroeconomic factor-related component (factor-related returns) and an idiosyncratic component specific to the individual asset (asset-specific returns).

This decomposition produces two return series, factor-related and asset-specific, for each instrument. Each series is used as the basis for the creation of a set of time series momentum portfolios using the methodology described above.

The factor-related time series momentum strategy generates a trading signal for each futures contract from its factor-related return, whereas the asset-specific time series momentum portfolio is built using a signal generated from the component of each futures contract return not explained by the factor model.

The first step in this process is to decompose the returns of each futures contract into factor-related and asset-specific components. We define the regression model to explain the factor-related price movement following Grundy and Martin (2001) and Chordia and Shivakumar (2002). The model is estimated for each futures contract for each month, using the current month and prior 59 months' returns. Estimating the model using a rolling regression allows us to identify the time varying factor-related return.

$$r_t^i = \beta_{0,t} + \sum_{n=1}^{N} \beta_{n,t} \Delta F_t^n + \varepsilon_t \tag{4.8}$$

Where r_t^i is the excess return of futures contract *i* in time period *t*, ΔF_t^n is the change in factor *n* in time period *t* and ε_t is the error term. The model has *N* factors. The regression coefficients $\beta_{0,t}$ and $\beta_{n,t}$ are the coefficients for the model estimated over the period *t-59* to *t*, where $\beta_{0,t}$ is the regression intercept and $\beta_{n,t}$ is the regression coefficient for factor *n*.

The factor-related return of each instrument at time *t* is then estimated as

$$frr_t^i = \beta_{0,t} + \sum_{n=1}^{N} \beta_{n,t} \Delta F_t^n \tag{4.9}$$

Where frr_t^i is the factor-related return of instrument *i*, at time *t*. The corresponding asset-specific return, asr_t^i, is then calculated as the difference between the excess return and factor-related return at time *t*.

$$asr_t^i = r_t^i - frr_t^i \tag{4.10}$$

We then form two alternative time series momentum portfolios using, alternately, factor-related returns and asset-specific returns (rather than raw excess returns) to generate the trading signal.

Under this construction, if time series momentum returns are entirely due to exposure to macroeconomic risk then only the portfolios formed on factor-related returns should yield positive payoffs. The cumulative returns are reported in Figure 4.4 and the summary statistics of the different portfolios are displayed in Table 4.8.[42]

Looking first at the diversified portfolio, it can be seen that statistically significant excess returns are generated by both sets of portfolios, factor-related (Panel B) and asset-specific (Panel C) futures returns over the full sample period and both sub-periods.[43] Over the full period, the portfolio formed on asset-specific returns generates an annual excess return of 9.92% compared to 5.74% for the portfolio formed on factor-related returns. Looking at the results over the two sub-periods, the portfolio formed on macroeconomic factor-related returns is consistent, with payoffs of 5.18% and 6.13% respectively. The asset-specific return portfolio shows a different pattern, with an excess return of 14.14% in the earlier period and 7.09% since 1980. For individual markets, all the sub-portfolios have positive returns for the asset-specific return portfolios and in all

[42] Results are reported from January 1956 as we use a 60 month period to decompose futures returns and a further 12 month formation period for the initial time series momentum signals.
[43] The signal generating process of the portfolios is quite different reflected in a full sample correlation coefficient of -0.06 for the diversified portfolios formed on factor and idiosyncratic returns.

but two cases these are statistically significant. The factor-related portfolio returns are quite different. While the equity and bond portfolios produce statistically positive returns over the full period, the FX return is only marginally positive and the commodity return is close to zero. Results are more mixed over the sub-periods where, while the majority of the returns are positive, only two are statistically significant.

Figure 4.4
Portfolio Formed on Explained and Unexplained Returns

The figure shows the natural logarithm of the cumulative excess return series of two global diversified time series momentum portfolio from January 1956 to September 2014. Portfolio Formed on Explained Returns is a time series momentum portfolio formed from signals based on the return of the underlying instruments explained by the macroeconomic model. Portfolio Formed on Unexplained Returns is a time series momentum portfolio formed from signals based on the unexplained (futures specific) return of the underlying instruments.

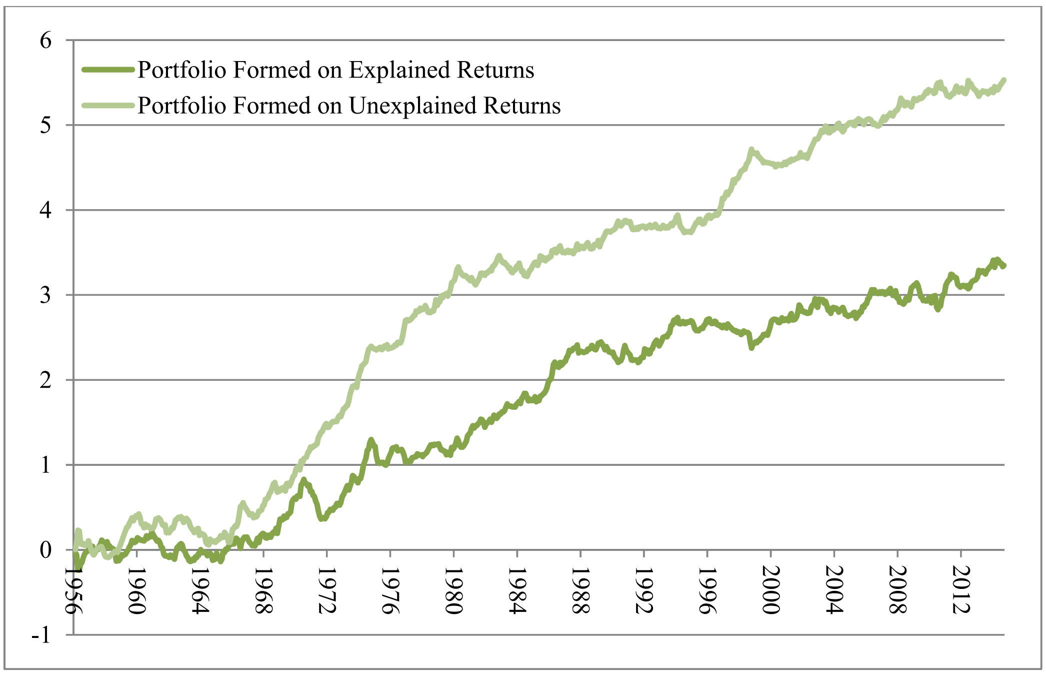


Table 4.8
Decomposition of Time Series Momentum Returns

In each panel the average annualised excess returns and t-statistics are presented across five portfolios and three time periods. The five portfolios consist of a diversified portfolio and four asset class sub-portfolios; equity indices, government bonds, FX and commodities. The results are presented for the period from January 1956 to September 2014 and two sub-periods; January 1956 to December 1979 and January 1980 to September 2014. The FX time series begins in August 19776 and the commodity in August 1956, all others begin in January 1956. Panel A presents the results of the standard time series momentum model, where trading signals are generated from raw excess returns. Panel B shows the return statistics of time series momentum portfolios formed from signals based on the return of the underlying instruments explained by the macroeconomic model. Panel C presents the results of time series momentum portfolios formed from signals based on the asset-specific return of the underlying instruments. Excess returns significant at the 5% level are shown in bold.

	Equity	Bonds	FX	Commodity	Diversified
Panel A: Portfolios Formed on Raw Returns					
1956-2014	**4.42**	**5.42**	**1.93**	**2.23**	**14.52**
	6.41	6.53	2.97	4.41	9.04
1956-1979	**3.16**	**5.82**	4.18	**1.90**	**13.79**
	3.37	4.49	1.68	2.05	5.49
1980-2014	**5.30**	**5.15**	**1.67**	**2.45**	**15.03**
	5.46	4.76	2.52	4.37	7.19
Panel B: Portfolios Formed on Economic Factor-Related Returns					
1956-2014	**3.02**	**2.14**	0.40	-0.03	**5.74**
	4.19	2.68	0.72	0.10	3.90
1956-1979	0.34	**5.42**	-5.48	-0.53	**5.18**
	0.44	3.99	-1.64	-0.41	2.17
1980-2014	**4.92**	-0.08	1.10	0.32	**6.13**
	4.93	0.13	1.78	0.68	3.30
Panel C: Portfolios Formed on Asset-Specific Returns					
1956-2014	**2.41**	**3.73**	1.05	**1.89**	**9.92**
	4.60	4.70	1.67	3.53	6.77
1956-1979	**4.09**	**3.36**	**6.23**	**2.65**	**14.14**
	4.25	2.89	2.09	2.49	5.40
1980-2014	**1.27**	**3.98**	0.47	**1.37**	**7.09**
	2.18	3.70	0.81	2.59	4.19

Note: The FX sub-portfolio begins in 1977, and so results for 1956-1979 are based on a three year sample.

4.7 Economic Uncertainty

Recent evidence on time series momentum has highlighted that the performance of the strategy tends to be below average for an extended period following financial crises (Hutchinson and O'Brien (2014)). Separately Bali *et al.* (2014) present evidence that economic uncertainty plays a role in explaining the cross-sectional deviation in the performance of hedge funds. In order to identify if macroeconomic uncertainty is the transmission mechanism linking macroeconomic factors and the results of Hutchinson and O'Brien (2014) we specify a model of economic uncertainty, based on Bali *et al.* (2014), where the time varying conditional volatility of a set of eight economic variables is used as a proxy for economic uncertainty.

Bali *et al.* (2014) define economic uncertainty as being a function of the time varying conditional volatility of the eight risk factors. The time varying conditional volatility is estimated using a vector auto regressive process to model the economic variables and a GARCH model to capture the asymmetric response of volatility to change in the economy.

The auto regressive model is given as:

$$[Z_t] = [\beta_0] + [\beta_n][Z_{t-1}] + [\varepsilon_t] \tag{4.11}$$

Where $[Z_t]$ is an 8x1 matrix of the values of the eight variables at time *t*. $[\beta_0]$ is an 8x1 matrix of regression constants and $[\beta_n]$ is an 8x8 matrix of regression coefficients. $[\varepsilon_t]$ is the matrix of regression errors at time *t*. After regressing the model over the time period January 1950 to September 2014, the expected volatility of each factor is estimated using a multivariate asymmetric GARCH model, specifically the Threshold-GARCH (TGARCH) model of Glosten *et al.* (1993). The asymmetry allows different responses to positive and negative shocks to be modelled. The TGARCH model is:

$$E\left[\varepsilon_{i,t}^2\right] \equiv \sigma_{i,t}^2 = \gamma_0^i + \gamma_1^i \varepsilon_{t-1}^2 + \gamma_2^i \sigma_{t-1}^2 + \gamma_3^i \varepsilon_{t-1}^2 D_{i,t-1} \tag{4.12}$$

$$D_{1,t} = 1 \; for \; \varepsilon_{i,t} < 0, 0 \; otherwise$$

Where $E\left[\varepsilon_{i,t}^2\right]$ is the expected value of the square of the error term of variable *i*, at time *t*. This is the conditional volatility, $\sigma_{i,t}^2$, of the instrument. γ_n^i is the coefficient *n* of variable *i*. $D_{i,t}$ is a dummy variable set to one for $\varepsilon_{i,t} < 0$ or zero otherwise. A positive value for γ_3^i indicates negative shocks cause higher volatility than positive shocks.

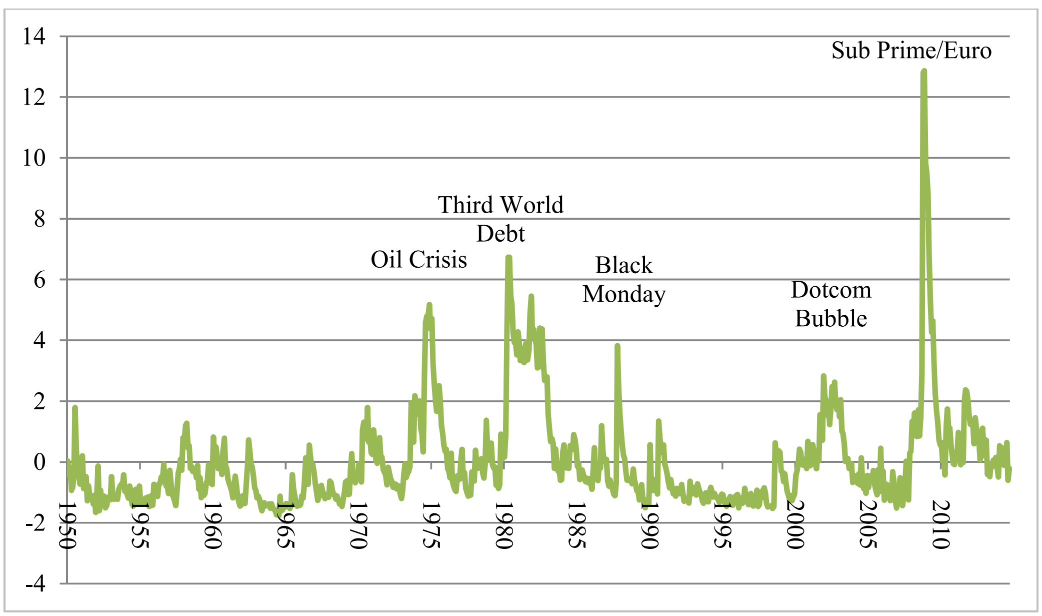
The final stage of the process combines the volatilities of the eight factors to generate an index of economic uncertainty. The volatilities of the factors are both persistent and cross correlated, allowing the use of principle component analysis. Following Bali *et al.* (2014) we use the first principle component to generate a linear function of the eight individual time series.

Our methodology differs from Bali *et al.* (2014) in two ways. Bali *et al.* (2014) use a recursive estimation procedure, whereas we use a single estimation for the full time period, which induces a look-ahead bias. The advantage of our approach is that it allows us to begin our analysis in 1950, maximizing the sample of available economic data.[44] While Bali *et al.* (2014) estimate all parameters simultaneously, we estimate the economic model separately from the T-GARCH volatility model.

The economic uncertainty index based on Bali *et al.* (2014) is reported in Figure 4.5. The measure varies through time, but peak economic uncertainty measured by the model closely corresponds to the financial crises identified in Hutchinson and O'Brien (2014).

Figure 4.5
Economic Uncertainty Index

The figure presents the measure of economic uncertainty used in this paper. The measure is based on the methodology defined in Bali *et al.* (2014). The major peaks, associated with the periods of highest uncertainty, are identified. The labels correspond to the financial crises identified Hutchinson and O'Brien (2014). The times series runs from January 1950 to September 2014.



To see the impact of economic uncertainty on the performance of time series momentum, we compare the performance in periods of high and low uncertainty over the full period and each of the sub-periods. The markets are defined as high or low uncertainty by

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[44] The recursive estimation approach requires an extended window of data, prior to the sample period (Bali *et al.* (2014) use 23 years). As our economic data set begins in 1950, incorporating a similar formation period eliminates much of the first sub-sample period.

comparing the level of economic uncertainty with its mean for the period.[45] [46] The results are shown in Table 4.9.

The diversified portfolio exhibits better performance in periods of below average uncertainty for both the full sample period (18.39% against 9.84%) and both sub-periods, (17.48% compared with 14.34% in the earlier period and 17.33% compared with 9.92% in the later period). This pattern is evident in the equity and currency markets, over both the full period and both sub-periods; although it should be noted the sample size for currencies is small in the earlier period, running from 1972 to 1979.

Table 4.9
Time Series Momentum Performance and Economic Uncertainty

The table reports the average annualised excess return for five time series momentum portfolios in periods of high and low risk. The portfolios consist of a diversified portfolio and four asset class sub-portfolios; equity indices, government bonds, FX and commodities. Uncertainty is measured using the economic uncertainty index set out in this paper based on Bali *et al.* (2014). A month is defined as high (low) risk if the value of the risk measure for that month is greater (less) than the average value for the sample period. The average return for high (low) risk periods is the mean of the excess return in all high (low) risk periods. The results are presented from January 1950 to September 2014 and over two sub-periods, January 1950 to December 1979 and January 1980 to September 2014. The FX time series begins in August 1972 and the commodity in August 1951; all others begin in January 1950. Excess returns are presented net of transaction costs and gross of fees. Statistically significant differences, calculated using a one tailed test, are indicated at confidence levels of 10% (*), 5% (**) and 1% (***).

	1950-1979			**1980 – 2014**			**1950-2014**		
	High	**Low**		**High**	**Low**		**High**	**Low**	
% Time	38.06	61.94		34.05	65.95		33.85	66.15	
Equity	3.66	5.89		1.46	7.35	***	2.36	6.66	***
Bonds	4.64	6.06		6.27	4.72		5.25	5.43	
FX	3.06	2.37		0.64	2.32		-0.08	2.92	**
Commodity	3.20	0.72	*	1.56	2.95		2.05	2.14	
Diversified	14.34	17.48		9.92	17.33	*	9.84	18.39	***

The results for government bonds and commodities are less consistent. The performance of the bond portfolio over the full period is marginally better when economic uncertainty is reduced, while it performs better in low uncertainty conditions in the earlier period and high uncertainty conditions in the later sub-period. The commodity portfolio again shows a different pattern, with similar performance under high and low uncertainty over the full periods and performing better in high uncertainty conditions in the first sub-period.

[45] As the mean uncertainty is a function of the sub-period, individual months can be assigned to different states depending on the mean of the period under investigation.
[46] Results are very similar when the analysis is based on the median of the series.

In order to further investigate the relationship between the returns and economic uncertainty a series of regressions were carried out based on the model

$$r_t^{tf} = \beta_o + \beta_1 U_{t-l} + \varepsilon_t \tag{4.13}$$

Where r_t^{tf} is the return of the diversified time series momentum portfolio at time t, and U_{t-l} is the value of the economic uncertainty index at time t - l. The variable l is the measure of the lag or lead of the uncertainty index relative to the return series. The test statistics of the regression coefficients for a range of values of l (-18 to 18) is displayed in Figure 4.5.

Figure 4.6
Time Series Momentum Returns and Economic Uncertainty

The excess returns of the diversified time series momentum portfolio was regressed against the Economic Uncertainty Index at a variety of lags/leads using the regression model $r_t^{tf} = \beta_o + \beta_1 U_{t-l} + \varepsilon_t$, where U_t is the value of the economic uncertainty index at time t and l is the lag (lead), ranging from -18 to +18 months. The figure displays the test statistics of the regression coefficientβ_1. The results of the lagged index appear to the left, and the lead index to the right. The times series run from January 1950 to September 2014.

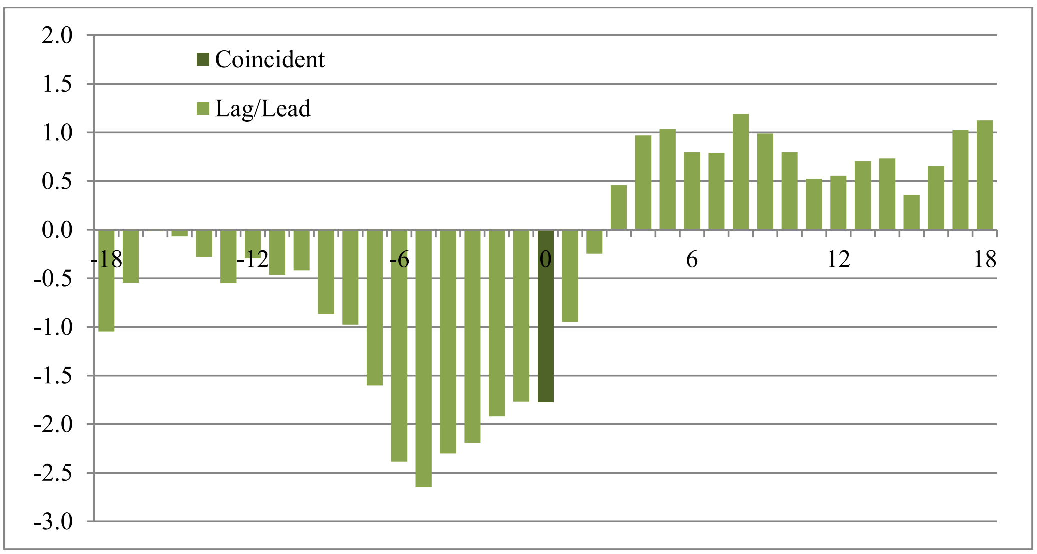


Figure 4.6 shows a statistically significant negative relationship between the returns to time series momentum and the uncertainty index in the contemporaneous month and for lags of up to six months. Following periods when economic uncertainty is low (high) the returns of the time series momentum strategy are higher (lower) than average. Given the association of economic uncertainty and periods following financial crises, this helps explain previous findings that time series momentum returns are below average in the period after financial crises (Hutchinson and O'Brien (2014)).

4.8 Conclusions

This article was motivated by two observations. First, CTAs have received large inflows of capital following the 2008 financial crisis. Second, investors' motivation for allocating to CTAs is often due to an expectation of performance in equity bear markets, without a consideration of performance in other market states, or the drivers of performance. We have shown that the returns to time series momentum are connected to the business cycle. Time series momentum earns positive returns in both expansions and recessions but the returns are especially strong in expansions. Whether we measure the business cycle using NBER data, GDP data or use interest rate spreads as proxies for short and long term fluctuations, our results are consistent. Returns are statistically significantly higher by between 5% and 8% in expansions. These findings dispel the notion that high returns to time series momentum are specific to equity market states.

Taken together our results provide a degree of clarity on the return drivers of time series momentum. Complementing Moskowitz *et al.* (2012) who document a behavioural driver, we find that there is a role for rational price theories to explain a portion of time series momentum profitability. We find that the returns are related to a set of macroeconomic factors that have been shown in the literature to be important in explaining the returns of traditional asset classes and hedge funds. Our results indicate that about 40 percent of the returns of time series momentum are due to time varying exposure to these macroeconomic variables, which are related to the business cycle. These findings are consistent with the conclusions of Chordia and Shivakumar (2002) for cross-sectional momentum, that a portion of the profitability of momentum strategies represents compensation for bearing time varying risk, consistent with rational asset pricing theories.

Finally, we note the interesting finding that the performance of time series momentum improves when economic uncertainty is diminished. This result provides a link between the finding of Hutchinson and O'Brien (2014), that time series momentum tends to perform less well than average following periods of financial crisis, and changes in the business cycle. Using a new methodology, we document that uncertainty is the transmission mechanism linking changes in the macroeconomic variables and changes in the performance of time series momentum following financial crisis

4.A Appendix: Data Sources

4.A.1 Equity Indices

The universe of equity indices has twenty components. Fourteen of these consist of data from developed markets, with future prices available from Datastream starting at various dates from January 1980 and derived forward prices generated from data provided by Global Financial Data prior to that. In each case Global Financial Data provides a total return index, which allows the yield to be calculated. This group consists of Australia (SPI200), Canada (TSX 60), Netherlands (AEX), France (CAC 40), Germany (DAX), Hong Kong (Hang Seng), Korea (KOSPI 200), Japan (Nikkei 225), United States (S&P 500), United Kingdom (FTSE 100), Spain (IBES 35), Italy (MIB), Sweden (OMX 30) and Switzerland (SMI).

The six additional indices are the three mid cap indices (Germany, Switzerland and United States) and three alternative indices for the US (Dow Jones, Russell 2000 and NASDAQ 100). We only include exchange traded future contract data for these indices.

4.A.2 Bond Indices

A total of thirteen government bond indices from six countries are used. Australia (10 and 3 year), Canada (10 year), United States (2, 5, 10 and 30 year), Germany (2 ,5, 10 and 30 year), Japan (10 year) and United Kingdom (10 year). Exchange data for these is from Datastream, starting on a variety of dates from January 1980. Data for eight of these is extended backwards using total return indices and short term yields from Global Financial Data.

4.A.3 Currencies

The universe of currency forwards consists of ten currencies. Forwards are created for all currency pairs from spot data and short term interest rates. The spot rates are sources from Datastream/MSCI from 1980 and, prior to that, from Global Financial Data. Although data is available back to 1920, currencies are only considered for inclusion and statistics provided from the end of the Bretton-Woods fixed rate system in 1971. The Euro and German Mark are spliced into one time series. The currencies included are Australia, Canada, Euro (Germany), Norway, New Zealand, Sweden, Switzerland, United Kingdom and United States.

4.A.4 Commodities

Twenty one commodities are included; Copper, Gold and Silver (COMEX), Light Crude Oil, Natural Gas, NY Heating Oil, Palladium, Platinum and RBOB Gasoline (NYMEX), Cocoa, Coffee, Cotton, Gas Oil and Sugar (ICE), Corn, Soya Bean Oil, Soya Bean Meal, Soya Beans and Wheat (CME) and Lean Hogs and Live Cattle (CBOT). The commodity data is entirely based on prices of exchange traded futures. As cost of carry data is unavailable it is not possible to accurately estimate forward prices prior to the availability of exchange traded futures. The commodity data from 1980 was sourced from DataStream while the earlier data was sourced from Commodity Systems Inc. (CSI). The Copper contract consists of a combination of the medium grade copper contract traded until l988 and the high grade copper contract traded since then, sourced from CSI and DataStream respectively.

4.A.5 Risk Free Rates

Short term interest rates are sourced from Global Financial Data due to more extensive coverage. The one month interbank rate (LIBOR or equivalent) is the preferred rate. When this is not available, the closest available interbank rate was used, and finally the central bank base rate.

4.A.6 Economic Factor Model

Table 4.10 shows the data sources used for the primary data used to define the economic factor model. All data is available from January 1950, with the exception of the yield of the 10 Year US Treasury Bond (constant maturity), which becomes available from 1952. The first two years of this time series were back filled using the US 10 Year Treasury Bond Yield from the same source.

Table 4.10
Macroeconomic Risk Model: Data Sources

This table lists the sources for the data items used in the economic analyses. It includes the primary data used to derive the factors of the economic uncertainty model and the items used to define the economic cycle. All data items listed in this section are available for download from the named website.

Data Item	Source
BAA and AAA rated US Corporate Bond Yields 3-Month US T-Bill Rate 10 Year Constant Maturity US Treasury Bond	www.federalreserve.gov/releases/h15/data.htm
The Aggregate Dividend Yield on the S&P 500 US CPI	www.econ.yale.edu/~shiller/data.htm
US GDP US GDP per capita	research.stlouisfed.org/fred2/
Excess Return on US stocks	mba.tuck.dartmouth.edu /pages/faculty/ken_french/data_library.html
Unemployment Rate	www.bls.gov/cps/lfcharacteristics.htm
NBER Economic Cycles	www.nber.org/cycles/cyclesmain.html

Chapter Five

Just a One Trick Pony? An Analysis of CTA Risk and Return

Abstract[47]

Recently a range of alternative risk premia products have been developed promising investors hedge fund / CTA like returns with higher liquidity, transparency and relatively low fees. The attractiveness of these products rests on the assumption that they can deliver similar returns. Using a novel reporting bias free sample of 3,419 CTA funds as a testing ground, our results suggest this assumption is questionable. We find that CTAs are not a homogenous group. We identify eight different CTA sub-strategies, each with very different sources of return and low correlation between sub-strategies. To illustrate the difficulty of modelling the strategies we specify recently identified alternative risk premia from the academic literature as factors to examine the sources of return of CTAs. We find that these premia fail to explain between 56% and 86% of returns. Our results suggest that, given the heterogeneity of CTAs, while these new products may deliver on liquidity, transparency and fees, investors expecting hedge fund / CTA - like returns may be disappointed.

[47] This paper has been accepted for publication in *The Journal of Alternative Investments,* expected issue, Vol. 20 No. 2.. The research reported in this paper has been presented at the FMA Europe conference, Lisbon, 2017. Lead author, John O'Brien, co-authors; Jason Foran, Mark Hutchinson and David McCarthy.

5. Just a One Trick Pony? An Analysis of CTA Risk and Return

5.1 Introduction

One of the fastest growing segments of the alternative asset management industry is alternative risk premia products. These offerings promise hedge fund like returns with higher liquidity, transparency and relatively low fees.[48] [49] The attractiveness of these products depends upon the assumption that it is possible to deliver similar returns to hedge funds. In this paper we test this assumption for one particular hedge fund classification by addressing two questions. First, does this particular classification of hedge fund actually follow a homogenous, easily modelled strategy? Second, are the returns of the hedge funds within this single classification easily modelled using alternative risk premia?

We address these questions using a novel dataset of Commodity Trading Advisors (CTAs) as our sample hedge fund classification. We specify CTAs as they are one of the longest established hedge fund classifications, with an extensive academic literature providing guidance on their sources of return. Recently this academic literature has been accompanied by advances in alternative risk premia products which seek to capture their characteristics. We are also fortunate in having a comprehensive dataset of funds going back to 1987 which has been carefully cleaned of reporting biases.

Our first finding is that CTAs represent more than a single homogeneous style. We utilise statistical clustering techniques to identify different types of CTA and classify them into eight sub-strategies. The different sub-strategies generally have low correlation between clusters, generating their returns from very different sources. Our second key finding, using alternative risk premia from the academic literature, is that it is difficult to model their returns. These alternative risk premia do not explain a large proportion of CTA returns, with the proportion of CTA portfolio returns explained by the premia ranging

[48] While there is no standard definition we use the term "alternative risk premia" to describe the portion of hedge fund / CTA returns explained by non-traditional systematic factors. We are aware that this definition is also associated by practitioners with the terms "alternative beta", "strategic beta", "smart beta" and "factor investing".
[49] It is difficult to gather data on alternative risk premia assets under management (AUM). Data from Morningstar for Smart Beta exchange traded products (which are predominantly equity related) gives an indication of the likely growth rates. AUM has jumped from \$100bn to over \$500bn between 2008 and 2015.

from 14% to 44%.[50] When we divide CTA returns into alternative risk premia exposure and alpha, we find that three of our eight CTA clusters generate alpha.

From a practitioner's perspective these results suggest attempts to capture the returns of CTAs face certain challenges. Since CTAs are a heterogeneous group it is difficult to reproduce their returns. Even sophisticated products which seek to track aggregate CTA performance are likely to have high tracking error due to the lack of a single identifiable style. Further, as noted, we find eight sub-strategies within our CTA universe. Given alternative risk premia from the academic literature represent a small proportion of the source of returns for each of these sub-strategies (ranging from 14% to 44%), it is difficult to make the case (at least for the specifications in this paper) that these alternative risk premia represent a close substitute for investing directly in CTAs.

The remainder of the paper is organised as follows: In the next section we review the literature and discuss how our results link to and extend the literature. In section 5.3 we describe our CTA dataset and the results of our clustering analysis. Next, in section 5.4, we describe the dataset and methodology we use to create our alternative risk premia. This is followed in section 5.5 by results on the alternative risk premia exposure of CTAs, using self-classification and statistical clustering. Finally, we conclude with a discussion of our key findings in section 5.6.

5.2 Literature Review

The literature on mutual funds and hedge funds has demonstrated that clustering is generally superior to self-classified styles for predicting cross-sectional past and future performance (Brown and Goetzmann (1997) and Brown and Goetzmann (2003)). The difficulty with self-classification is that it provides latitude for funds operating in the same classification to conduct divergent behaviour and evidence for mutual funds finds that many funds within the same self-classification have quite different return generating processes (Brown and Goetzmann (1997)). Our paper compliments Kazemi and Li (2009) who divide CTAs into systematic and discretionary sub-classifications, showing the very different characteristics of these groups. In this paper we use clustering

[50] In comparison for actively managed equity mutual funds risk premia fail to explain between 3% and 22% of portfolio returns (Carhart (1997)).

techniques to put CTAs into classes based upon differences in how the funds generate their returns.

In doing so we add to a prior literature on the performance of CTAs, which is generally positive (e.g. Schneeweis *et al.* (1991), Schneeweis *et al.* (1997), Edwards (1998), Liang (2003), Gregoriou *et al.* (2005), Kazemi and Li (2009), Gregoriou *et al.* (2010), Arnold (2012) and Schneeweis *et al.* (2013)), with the exception of two early studies (Elton *et al.* (1987) and Elton *et al.* (1990)) and a recent paper ((Bhardwaj *et al.* 2014)). There is also related literature which highlights the diversification benefits of CTAs as part of a broader institutional portfolio (for example Fung and Hsieh (2000), Edwards and Caglayan (2001), Fung and Hsieh (2001) and Mulvey (2012)), highlighting the strong performance in equity and bond bear markets.

Advances in the alternative risk premia literature have focused on identifying risk premia jointly across all asset classes, that are constructed by forming portfolios of futures and options (in a manner consistent with CTAs) using signals generated from a range of variables. These global risk premia can be broadly classified as time series momentum, carry, value and options based. Research on the performance and risks of global time series momentum (typically known as trend following in the investment industry) is emerging in the literature (see, Baltas and Kosowski (2013), Hutchinson and O'Brien (2014) and Hutchinson and O'Brien (2015)). Despite carry historically being associated with foreign exchange (see (Menkhoff *et al.* 2012a) for a recent example) research has emerged focusing on basis (a measure of commodity futures carry) in commodities (Erb and Harvey (2006) and Gorton and Rouwenhorst (2006)) and fixed income (Duarte *et al.* (2007)). Research on equity markets has traditionally found predictive power for the dividend yield (a measure of equity carry) though it has varied over time (see Ball (1978) for an early study and (Dangl & Halling 2012) for recent evidence of time varying predictability). Unifying research on carry in different asset classes, (Koijen *et al.* 2013) present evidence documenting the prevalence of carry as an alternative risk premia effect across all four asset classes. Likewise, while traditionally value is associated with equity markets, Asness *et al.* (2013)document the power of relative value across a wide range of asset classes. Finally, perhaps the first researchers to utilise options based factors for a CTA trading strategy were Fung and Hsieh (2001). They document the power of their options based factors in explaining the performance of a wide range of hedge fund trading strategies (Fung and Hsieh (2004)). We build upon this literature by specifying these alternative risk premia to identify the proportion of CTA returns which is coming from non-traditional systematic sources.

5.3 Data and Sample

5.3.1 CTA Returns Data

We use the BarclayHedge CTA database as our source of CTA returns data due to its depth of coverage. The BarclayHedge database includes both live funds and a graveyard file containing the returns of funds which have ceased reporting to BarclayHedge, eliminating survivorship bias.

Table 5.1
Database Cleaning and Sample Size

The table shows the number of funds remaining in the sample after each successive stage of data filtering.

	Funds Removed	Funds Remaining
BarclayHedge Live and Dead CTA Databases: Full Sample		5199
Remove Fund of Funds and Indices	228	4971
Remove non-USD denominated funds	504	4467
Remove highly correlated (>0.99) funds	314	4153
Remove backfilled funds and pre-2002 non index funds	692	3461
Remove funds without AUM: Sample for performance analysis	42	3419
Remove funds with less than twelve return months: Sample for cluster analysis	950	2469

A number of filters are applied to the data to ensure it is representative of investors' experience of investing in CTAs. First, funds of funds are removed as are any indices, leaving 4,971 funds. As is standard, we remove all non-US dollar denominated funds, focusing on CTAs which are denominated in US dollars. Funds which do not report net of fees, or report at quarterly intervals are also excluded.

Our next step is to identify and remove duplicate shares. Following Jorion and Schwarz (2014) we use a return based filter to avoid duplicate share classes. If two programs with the same management company have a correlation of 0.99 or higher, then the program with the earliest start date is retained.

Finally we need to address backfill bias. Recent academic attention has focused on how to address this bias without introducing further bias to the study. For example, Bhardwaj *et al.* (2014) and Getmansky *et al.* (2015) remove any observations prior to the "date added" field in the TASS database. However, subsequent evidence by (Jorion & Schwarz 2014) Jorion and Schwarz (2014) indicates that this approach is likely to overstate backfill bias, as many funds in TASS in fact report to HFR at an earlier date. Using TASS is further complicated by the merger of TASS with Tremont in the late 1990s. The "date added" field in the TASS database for the Tremont funds is not the date the funds were added to Tremont but the date they were merged with TASS, which is much later (Fung and Hsieh (2009)). Whereas for HFR the earliest add date is May 1996, which is most likely to represent the date HFR started to collate this variable (Jorion and Schwarz (2014)).

In our study we take a novel approach to backfill bias. Since 2002, BarclayHedge have collated a "date added" variable for each fund, indicating when the fund was added to the database. This allows us to easily remove all backfilled returns for these funds, prior to the date they were added to the database. For pre-2002 data BarclayHedge provided us with the constituents of the BarclayHedge CTA Index. The BarclayHedge CTA Index is equal weighted and rebalanced at the beginning of each year. To qualify for inclusion in the index an advisor must have four years of prior performance history and must be reporting to BarclayHedge at the beginning of the year. Additional programs introduced by qualified advisors are not added to the Index until after their second year.

As constituents are added at the beginning of each year, in order to qualify for inclusion in the index, a fund would have to be already reporting to BarclayHedge. Hence, pre-2002 we only include a fund's returns in our sample, if they have, or have in the past, been constituents of the BarclayHedge CTA Index.[51] This leaves us with a sample of 3,461 funds. As we need AUM data for creating AUM weighted portfolios of CTAs, removing funds which do not report this information leaves us with 3,419 funds.[52] Finally, in the paper we conduct statistical clustering to identify common styles of CTA. This technique requires a minimum of twelve months of returns. Interestingly, removing

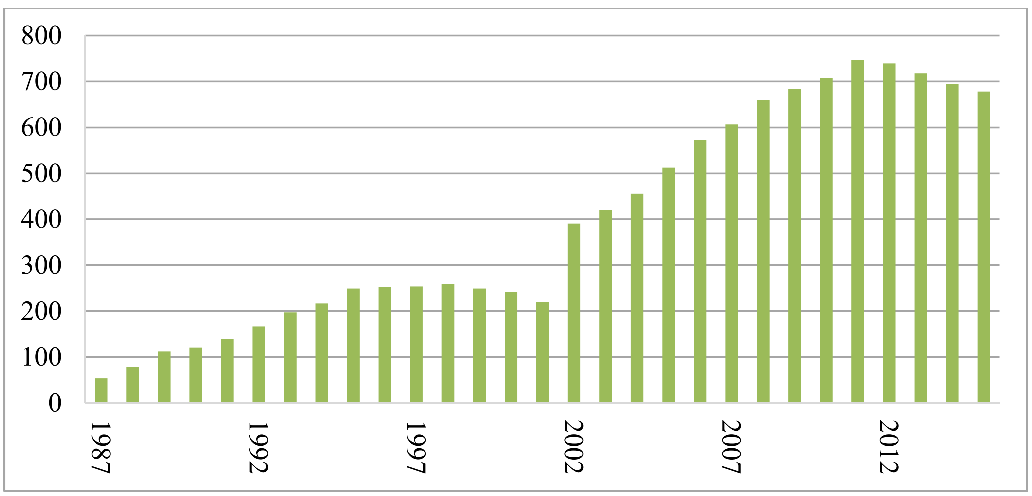
[51] There are 19 funds that are listed in the BarclayHedge CTA Index constituent list which are not in the database. BarclayHedge clarified that there are a number of funds who provide them with data solely for index calculation purposes, with whom they have an agreement not to re redistribute their data. A number of funds cease reporting to the database for a period before resuming reporting, leaving a gap in their return history. In this instance we remove all returns prior to the fund resuming reporting.

[52] There is evidence in the literature that the reported AUMs in hedge fund databases are not reliable. Funds tend not to update them and smaller funds may also have an incentive to inflate them. For robustness we report all results for equal weighted as well as AUM weighted portfolios.

funds with fewer than twelve months eliminates a further 950 funds. The quite considerable drop off in sample size for this step demonstrates the high attrition rate of CTAs who newly report to the database.[53]

Figure 5.1 shows the number of funds within our CTA sample from January 1987 to July 2015. There is a notable increase in funds from 2003 onward when BarclayHedge introduce their "date added" variable. While we recognise that our pre-2002 utilisation of constituent lists will introduce a downward bias to our performance results, as it excludes non-backfilled fund returns which are not in the index, our preference is to be conservative in providing performance estimates.

Figure 5.1
CTA Data Universe: January 1987 to July 2015
The figure shows the size of the CTA dataset of clean returns over the analysis period.



The descriptive statistics of the CTA dataset are reported in Table 5.2. For the full sample, from January 1987 to July 2015, an equal weighted portfolio of all CTAs earned annualised mean returns of 7.85% per annum, whereas an AUM weighed portfolio (rebalanced monthly using prior month reported AUM) of all CTAs earned 9.00% per annum. Post January 1994 returns are 5.40% per annum for the equal weighted portfolio and 7.70% per annum for the AUM weighted portfolio of CTAs. It is also notable that the volatility for the later sample is considerably lower, and Sharpe ratios are comparable

[53] Removing funds with fewer than twelve months of returns upward biases the average returns of the sample used in the clustering results by 0.035% per month. These short return history funds earn an average monthly return of -0.49%.

in both periods at 0.38 (0.49) and 0.37 (0.56) for the equal weighted (AUM weighted) portfolios.

Table 5.2
CTA Performance: January 1987 to July 2015

The table shows the summary performance figures for funds in the BarclayHedge CTA database. Summary performance measures are presented for both equal (Panel A) and AUM (Panel B) weighted portfolios. Annual return is the annualised average monthly return. Volatility is the annualised monthly standard deviation. Sharpe ratio is the annualised monthly return in excess of the risk free rate, divided by the volatility.

	1987 – 2015	1994-2015
Panel A: Equal Weighted		
Annual Return (%)	7.85	5.40
Volatility (%)	11.35	7.26
Sharpe Ratio	0.38	0.37
Panel B: AUM Weighted		
Annual Return (%)	9.00	7.70
Volatility (%)	11.20	8.80
Sharpe Ratio	0.59	0.56
Annual Risk Free Rate (%)	3.36	2.61

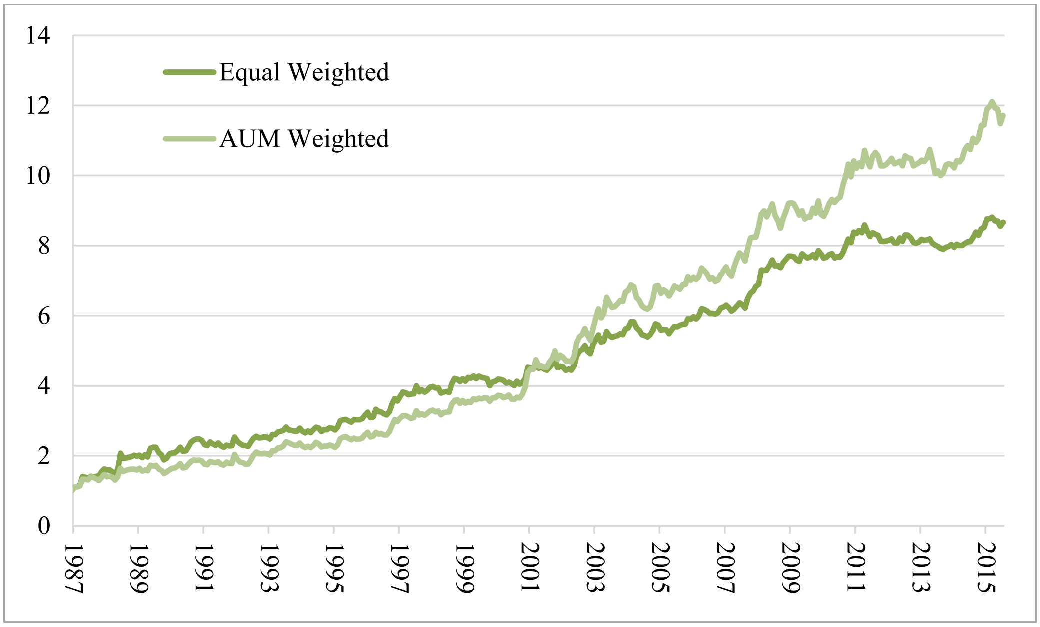
We also report cumulative returns in Figure 5.2. Interestingly, the equal weighted portfolio outperforms up to 2001, whereas from 2002 onward the AUM weighted portfolio outperforms.

5.3.2 Clustering Results

We next move on to examine portfolios formed using robust statistical clustering. The literature on mutual funds and hedge funds has demonstrated that clustering is generally superior to self-classified styles for predicting cross-sectional past and future performance (Brown and Goetzmann (1997) and (Brown & Goetzmann 2003)). Self-classification provides great latitude for funds to conduct widely divergent behaviour for funds operating in the same classification and evidence for mutual funds (which are subject to much stricter regulation than hedge funds) indicates that many funds are misclassified (Brown and Goetzmann (1997)). The advantage of clustering is that it objectively puts funds into classes based upon styles characterized by how the funds generate their returns.

Figure 5.2
CTA Cumulative Returns: January 1987 to July 2015

The figure shows the cumulative average return of the hedge funds in the Barclay Hedge CTA database. Cumulative returns are created for portfolios of CTAs which are equal weighted (Equal Weighted) and weighted by assets under management (AUM Weighted).



As noted earlier, in order to be included in our clustering approach funds must have a minimum of 12 observations. Our sample is divided into eight clusters following Brown and Goetzmann (1997).[54] We carry out clustering as an iterative process. First the exposures (correlations) of each fund to the risk premia are estimated. The clusters are initialised by assigning funds with common risk premia correlation into the same cluster. Next we calculate the time series of the average cross-sectional returns of each cluster. The next step is to estimate the correlation between each fund's return and each cluster's return. Using these correlations we reassign funds to the cluster with which they have the highest correlation. The process is repeated until no funds change cluster.

Table 5.3 reports the reallocation of CTAs from their self-reported classification to the eight clusters. For most of the clusters naming is straightforward as they are closely aligned to a well-known industry style. However for several of the fund clusters there is

[54] Choosing the number of clusters is a non-trivial issue. Choosing more clusters allows for more granular analysis of CTA sub-strategies, but risks introducing noise. While we follow Brown and Goetzmann (1997) who choose eight to analyse equity mutual funds (a far more homogenous group of funds than CTAs) we also repeated all of our analysis with as few as two clusters. These results, which are available from the authors on request, demonstrate the robustness of our key findings (low risk premia explanatory power and low cluster cross correlation) to the choice of the number of clusters.

no obvious match to a commonly accepted industry style. Hence, we name the clusters of funds based upon a combination of (1) their correlation with the average returns of the self-classified series, (2) the original self-classification of the majority of funds in the cluster, and (3) the fund clusters alternative risk premia exposures (reported in Table 5.3).

Table 5.3
The Relationship between Self-classification and Clusters

The table shows the re-allocation of CTAs from the initial self-allocated style to the eight clusters defined in this paper. For each self-classified category, the number of CTAs allocated to each cluster is given. Self-classifications with fewer than ten funds are not reported.

	Number of CTAs	Diversified Trend	Longer Term Trend	Shorter Term Trend	Fundamental Value	Fundamental Diversified	Fundamental Carry	Discretionary	Option Strategies: Short
Undefined	40	4	6	5	4	3	4	5	9
Arbitrage	48	3	3	3	12	6	4	6	11
Discretionary	46	7	11	3	2	4	6	6	7
Fundamental - Agricultural	83	14	7	7	7	13	17	6	12
Fundamental - Currency	89	10	13	13	10	15	8	14	6
Fundamental - Diversified	137	31	14	13	14	28	11	16	10
Fundamental - Energy	28	4	3	5	5	2	4	2	3
Fundamental - Financial/Metals	91	11	5	12	17	11	7	18	10
Option Strategies	208	9	10	7	19	24	7	5	127
Stock Index	196	12	17	23	43	27	24	12	38
Systematic	61	12	6	11	3	9	10	5	5
Technical - Agricultural	18	1	2	1	1	7	0	4	2
Technical - Currency	263	17	27	53	44	23	27	50	22
Technical - Diversified	866	379	124	90	46	50	33	112	32
Technical - Energy	19	2	1	3	3	5	3	1	1
Technical - Financial/Metals	250	49	34	37	26	23	29	30	22
Technical - Interest Rates	20	2	1	5	1	2	3	2	4
Number of CTAs		568	286	294	258	256	199	296	323

The largest category, by number of funds, is Diversified Trend which is comprised mainly of the BarclayHedge "Technical-Diversified" category, while the smallest grouping is Fundamental Carry, which includes funds from a broad range of BarclayHedge categories and is positively correlated to the carry alternative risk premium. The Longer Term Trend category is comprised principally of funds listed in

BarclayHedge's "Technical-Diversified" category and is correlated with the time series momentum alternative risk premium, itself a relatively longer duration signal. The Shorter Term Trend category is correlated with the option risk premium which appears to capture shorter term trend following effects. The Fundamental Value category is correlated with the value risk premium and has a negative relationship with the carry risk premium. The Fundamental Diversified category is comprised principally of BarclayHedge "Fundamental - Diversified" category funds and is related to the value, carry and option risk premia. Option Strategies: Short is made up predominantly of BarclayHedge "Option Strategies" funds and is negatively related to the options risk premium. Finally, Discretionary funds are comprised of a mixture of technical and fundamental funds, with no obvious match to the BarclayHedge categories or the alternative risk premia.

The descriptive statistics of our eight clusters (both equal and AUM weighted) are reported in Table 5.4. The highest returns are generated by Diversified Trend and Fundamental Carry in the full sample from January 1987 to July 2015, while Diversified Trend and Longer Term Trend generate the highest returns from January 1994 to July 2015. Fundamental Value and Option Strategies earn the lowest returns in both sample periods. The largest AUM is in the Diversified Trend, Longer Term Trend and Fundamental Diversified clusters.[55] The median correlation between the return of each fund in a cluster and the average return for that cluster ranges from 0.40 for Fundamental Carry to 0.68 for Diversified Trend. Looking next at portfolios weighted by AUM, in Panel B, we can see that performance is higher for Diversified Trend, Shorter Term Trend and Fundamental Diversified, whereas for the remaining clusters performance is lower than their equal weighted counterparts.

[55] AUM data is skewed by several relatively large funds. As at July 2015 greater than 60% of total AUM is invested in the ten largest CTAs.

Table 5.4
Descriptive Statistics of CTA Clusters

The table reports the summary statistics of the CTA clusters. The average annual return (Ret), annualized volatility (Vol) and Sharpe ratio (SR) is shown for each cluster. Results are reported for the full period, January 1987 to July 2015 and the period January 1994 to July 2015. Panel A shows the statistics for an equal weighted portfolio of CTAs and Panel B for an AUM weighted portfolio. The total number of funds (sample size) in the cluster and the AUM (USD billion as at July, 2015) are reported in Panels A and B respectively. In addition, Panel A reports the median correlation between the returns of each fund in a cluster and the average return for that cluster.

	Median Corr.	**No. of funds**	**Ret (%)**	**Vol. (%)**	**SR**	**Ret. (%)**	**Vol. (%)**	**SR**
			1987 - 2015			1994 - 2015		
Panel A: Equally Weighted Performance Statistics								
Diversified Trend	0.68	566	11.13	17.61	0.45	8.27	13.42	0.42
Longer Term Trend	0.59	281	8.35	14.87	0.34	7.48	13.25	0.37
Shorter Term Trend	0.54	293	7.10	15.07	0.25	6.40	11.37	0.34
Fundamental Value	0.40	258	2.94	13.04	-0.03	3.13	11.35	0.05
Fundamental Diversified	0.45	254	8.57	16.84	0.31	3.30	8.60	0.08
Fundamental Carry	0.40	199	8.81	13.58	0.41	5.21	8.23	0.32
Discretionary	0.47	295	6.12	7.92	0.36	4.64	6.76	0.31
Option Strategies: Short	0.49	323	4.20	12.74	0.07	1.33	10.97	-0.11
Panel B: AUM Weighted Performance Statistics								
		AUM ($bn)	Ret (%)	Vol. (%)	SR	Ret. (%)	Vol. (%)	SR
Diversified Trend		65.5	11.28	16.57	0.48	9.79	14.37	0.50
Longer Term Trend		164.1	6.25	11.12	0.26	4.84	8.80	0.26
Shorter Term Trend		3.0	10.59	13.55	0.54	8.50	8.26	0.73
Fundamental Value		1.6	2.36	9.00	-0.10	2.10	7.88	-0.06
Fundamental Diversified		90.6	7.58	14.35	0.30	3.71	9.38	0.12
Fundamental Carry		3.5	3.18	15.28	-0.01	3.97	9.78	0.14
Discretionary		12.1	5.43	6.88	0.31	3.77	5.49	0.22
Option Strategies: Short		2.9	4.40	13.36	0.08	0.66	9.06	-0.21

The correlations between the different clusters are reported in Table 5.5. Unsurprisingly, Diversified Trend, Longer Term Trend and Shorter Term Trend are all quite highly correlated, with coefficients ranging from 0.35 to 0.64. Shorter Term Trend is also reasonably highly correlated with Fundamental Carry and Discretionary, highlighting that even those funds classified as non-trend, appear to share characteristics with shorter term trend followers.

Table 5.5
Correlation of Cluster Returns

The table shows the correlation between the returns of the eight CTA clusters over the period January 1994 to July 2015. The results are shown for equal weighted (Panel A) and AUM weighted (Panel B) cluster performance.

	Diversified Trend	**Longer Term Trend**	**Shorter Term Trend**	**Fundamental Value**	**Fundamental Diversified**	**Fundamental Carry**	**Discretionary**	**Option Strategies: Short**
Panel A: Equal Weighted Performance								
Diversified Trend	1.00	0.53	0.64	-0.01	-0.07	0.36	0.44	-0.13
Longer Term Trend		1.00	0.35	0.01	0.02	0.10	0.19	0.00
Shorter Term Trend			1.00	0.04	-0.10	0.30	0.40	-0.19
Fundamental Value				1.00	-0.26	0.10	0.00	-0.04
Fundamental Diversified					1.00	-0.08	-0.16	0.10
Fundamental Carry						1.00	0.18	0.01
Discretionary							1.00	-0.23
Option Strategies: Short								1.00
Panel B: AUM Weighted Performance								
Diversified Trend	1.00	0.40	0.60	-0.03	0.00	0.31	0.26	-0.06
Longer Term Trend		1.00	0.19	0.19	0.17	0.10	0.04	0.00
Shorter Term Trend			1.00	0.11	-0.03	0.27	0.23	-0.10
Fundamental Value				1.00	0.07	0.04	-0.01	-0.03
Fundamental Diversified					1.00	-0.02	-0.05	0.19
Fundamental Carry						1.00	-0.01	0.03
Discretionary							1.00	-0.05
Option Strategies: Short								1.00

The clustering of CTAs has revealed a deeper and differentiated analysis of CTA returns. The results of these analyses have two major implications for practitioners. First, we find that the correlation between different clusters is low. This heterogeneity introduces major challenges to any attempt to model their returns, as there is no single identifiable strategy. Second, historically the performance of these clusters has been very different. Generally the returns of funds in the trend categories have been higher, accompanied by higher volatility, whereas the non-trend strategies typically have lower volatility and returns. Due to the higher historical returns, trend funds have also attracted the largest AUM. One needs to be aware of these characteristics when analysing CTA returns.

In the next section, to illustrate the difficulty in modelling the returns of the CTA clusters, we use three recently published futures based alternative risk premia (carry, value and time series momentum) and an options based risk premium, which has historically been shown to be correlated with the returns of CTAs. The result of the analyses will demonstrate the practical challenge of implementing futures and options based portfolios to replicate CTA returns.

5.4 Alternative Risk Premia

5.4.1 Futures Data

In this paper we use four alternative risk premia, recently specified in academic literature, to capture the sources of CTA returns. To minimize potential data snooping bias we use the risk premia as published in the academic finance literature.[56]

Three of the alternative risk premia are constructed based on the specifications provided in the literature and the fourth is downloaded from David A. Hsieh's data library. In each case, the alternative risk premium is defined as the returns of a portfolio of underlying futures instruments, constructed from signals defined in the source literature. The portfolios are built from a combination of exchange traded futures and forward prices derived from spot data. We use a consistent data universe across all three alternative risk premia and follow the most common usage in the underlying literature when deciding on details. The data is from Thomson Reuters unless otherwise stated.

The number of equities indices typically used in the literature range from nine (Moskowitz *et al.* (2012)) to eighteen (Asness *et al.* (2013)). We use universe of twelve, limiting the sample to one index from each country and to those with exchange traded data available over the majority of our sample period. The alternative risk premia portfolios for government bonds are exclusively created from synthetic futures, following both Asness *et al.* (2013) and Koijen *et al.* (2013). The data set consists of eight 10-year government bond futures. All commodity prices are based on exchange traded futures. The universe consists of twenty-two futures pairs, consisting of all instruments used in one or more of the original papers, with the exception of sugar, where we are unable to source data. For commodities the Thompsons/Reuters data is

[56] Data snooping refers to the risk of yielding misleading inferences when statistical tests are performed **after** analysing the data. The risk being that while historical model fit is high the patterns in the data are spurious.

augmented with CSI data for some earlier periods. Finally, we specify synthetic futures for all currency prices. We use a universe of ten currencies and exclude the pre-Euro legacy currencies following both Moskowitz *et al.* (2012) andAsness *et al.* (2013).

As noted above, portfolios and alternative risk premia are created from continuous cumulative excess return series for each of the instruments. Two methods are used to create these series. The first takes the price series for individual futures contracts trading on an exchange and combines these to produce a continuous excess return series. The second approach creates a synthetic return series by combining the underlying spot price, yield and risk free rate.

The continuous return series created from futures is derived from the monthly price series. For each month, the return for that month is the return of the nearest to deliver contract, which trades for the full month. In effect, this means we are rolling contracts on the last day of the month prior to the delivery month.

In the case of synthetic forwards, the excess return is defined as a function of spot price, yield and risk free rate. The excess return from buying a forward contract at the start of a month and holding it to month end, er_1, is given by:

$$er_1 = (1 + r_1)\left(\frac{1 + q}{1 + r_f}\right)^{(1/12)} - 1 \tag{5.1}$$

where r_1 is the (spot) price return for the month, r_f is the one month risk free rate, and q is the annualized yield.

Table 5.6 reports descriptive statistics of the futures data used in the study. In total we specify twenty-two commodity futures, twelve equity index futures, eight 10-Year bond futures and nine currency pairs. However, data is not available for all equity indices and commodities pre-January 1994, so for the earlier time period we have a reduced sample of nine equity index futures and thirteen commodity futures, in addition to the bond and currency data.

Table 5.6
Futures Data

The table lists the futures contracts included in the portfolios used to generate the risk alternative risk premia used in this study. Each future is listed with its average annual excess return, volatility and the date first included in the portfolio. The futures are divided into four classes; Commodities, Government Bonds, Equity Indices and currencies. All data series end in July 2015.

	Start Date	Annual Excess Return	Annual Vol.		Start Date	Annual Excess Return	Annual Vol.
Commodity Futures				*Equity Index Futures*			
COCOA	Jan. 87	-2.86	29.51	SPI 200-Australia	Jan. 94	3.82	12.84
COFFEE	Jan. 87	-6.54	37.84	S&P TSX60-Canada	Jan. 94	5.68	15.29
CORN	Jan. 87	-6.05	27.37	SMI – Switzerland	Jan. 87	6.25	16.74
COTTON	Jan. 87	-3.20	27.45	DAX-Germany	Jan. 87	3.74	21.38
LIVE CATTLE	Jan. 87	7.78	14.30	IBEX 35-Spain	Jan. 87	3.82	21.51
LEAN HOGS	Jan. 87	-1.96	26.03	CAC 40-France	Jan. 94	4.30	18.76
SOYABEANS	Jan. 87	4.02	24.13	FTSE 100-UK	Jan. 87	3.26	15.38
WHEAT	Jan. 87	-0.44	26.86	HANG SENG-Hong Kong	Jan. 87	8.50	26.57
BRENT CRUDE	Jan. 94	8.81	31.48	MIB-Italy	Jan. 94	1.94	22.25
GAS OIL	Jan. 94	7.60	31.80	NIKKIE 225-Japan	Jan. 87	-0.14	19.51
NY HEATING OIL	Jan. 87	9.67	35.90	AEX-Netherlands	Jan. 87	5.24	19.60
LIGHT CRUDE	Jan. 87	4.63	32.13	S&P 500–US	Jan. 87	6.25	15.05
NATURAL GAS	Jan. 94	-18.84	50.66				
ALUMINIUM	Jan. 94	-3.82	19.68				
SILVER	Jan. 87	-0.02	28.18				
GOLD	Jan. 87	0.13	15.53	*Currency Forwards*			
COPPER	Jan. 94	6.26	26.03	AUD/USD	Jan. 87	-2.91	11.57
NICKEL	Jan. 94	3.18	34.82	CAD/USD	Jan. 87	-0.84	7.56
LEAD	Jan. 94	3.21	28.69	CHF/USD	Jan. 87	-0.46	11.38
PLATINUM	Jan. 87	4.22	22.21	EUR/USD*	Jan. 87	-0.12	10.67
TIN	Jan. 94	5.63	24.06	GBP/USD	Jan. 87	-1.84	9.83
ZINC	Jan. 94	-2.64	25.71	JPY/USD	Jan. 87	1.37	11.08
				NOK/USD	Jan. 87	-1.56	10.89
Government Bonds				NZD/USD	Jan. 87	-3.89	11.88
Australia-10Y	Jan. 87	3.99	9.97	SEK/USD	Jan. 87	-0.47	11.39
Canada-10Y	Jan. 87	3.65	9.24				
Switzerland-10Y	Jan. 87	2.29	6.28				
Denmark-10Y	Jan. 87	4.42	9.27				
Germany-10Y	Jan. 87	2.92	7.01				
UK-10Y	Jan. 87	3.24	8.93				
Japan-10Y	Jan. 87	2.64	8.56				
US-10Y	Jan. 87	3.08	9.14				

* DEM/USD prior to the introduction of the Euro in Jan 1999

5.4.2 Methodology

In selecting the methodology to create the alternative risk premia, our goal is to use a uniform approach where possible, minimizing potential data snooping biases. In consequence where details differ in the literature, we take the simplest formulation. We initially create alternative risk premia at the asset class level, where each asset is equal dollar weighted, before combining asset class alternative risk premia into a final alternative risk premium, where the asset classes risk premia are aggregated using an equal volatility weighting.[57]

There are typically some variations in the literature in portfolio construction. We select a consistent methodology based on the simplest formulations. In consequence, following Asness *et al.* (2013) and Koijen *et al.* (2013), we do not adjust for volatility in individual assets (though we do at the asset class level) and look at the sign of the signal (long or short), not at its magnitude (following Moskowitz *et al.* (2012)). In effect the dollar value of each asset held in an asset class portfolio at a given time is the same. The market neutral portfolios are scaled so that at any time;

$$\sum w_i^{long} = -\sum w_i^{short} = 1 \; and \; |w_i| = \frac{2}{N_c} \tag{5.2}$$

w_i^{long} is the weight of instrument *i* if a long position is held in that instrument, w_i^{short} is the weight of instrument i if a short position is held in that instrument and N_c is the number of instruments in the asset class. The time series momentum portfolios are scaled so that for any month, if long positions were held in all assets the sum of the weights would equal one, that is

$$\sum |w_i| = 1 \; and \; |w_i| = \frac{1}{N_c} \tag{5.3}$$

where w_i is the weight of instrument i and N_c is the number of instruments in the asset class.

5.4.2.1 Value

There is no single measure of value that can be used consistently across different asset classes and consequently we use a variety of formulations to generate the value alternative risk premia across the four asset classes. However, in each case, we closely follow the methodology used in Asness *et al.* (2013). For equity indices, we use the previous month's market-to-book ratio for the MSCI index of the country as our measure of value. Equity indices with the highest (lowest) market-to-book ratio are considered to be relatively over (under) valued. For bonds, we use the 5-year change in the yields of 10-year bonds as our value measure. Bonds with the highest (lowest) change in yields

[57] By volatility weighting at the asset class level we ensure that there is an equal risk allocation to asset classes with very different volatilities (for example equities and bonds).

are considered to be most under (over) valued. For commodities we use the five year change in spot price, where commodities with the highest (lowest) five year return are considered to be relatively over (under) valued. Finally for FX we use the five year change in purchasing power parity as our measure of relative valuation.[58]

Having identified our measure of value for each asset class we then form market neutral long/short portfolios at the asset class level which are long (short) relatively low (high) value assets.

5.4.2.2 Carry

The carry alternative risk premium is constructed following Koijen *et al.* (2013) and is similar to other methods found in the literature, such as those used by Bhardwaj *et al.* (2014) and Gorton *et al.* (2013). Koijen *et al.* (2013) find that carry predicts returns both in the cross-section and time series for a variety of different asset classes including global equities, bonds, currencies, and commodities. Accordingly, it is an appropriate candidate as an alternative risk premium to explain CTA performance. Koijen *et al.* (2013) define the basic measure of carry as

$$C_t = \frac{S_t - F_t}{F_t} \tag{5.4}$$

where C_t, S_t and F_t are the carry, spot price and future price respectively of an asset at time *t*. As the time to delivery can vary between assets, including those within the same class, the raw measure is annualized to allow consistent comparisons across assets. While the spot rate for financial assets is well known, the spot rate for commodities is less certain. Therefore, following Koijen *et al.* (2013), we use the two nearest futures as the basis for calculating commodity carry. We are able to apply a consistent approach for all asset classes to create the carry risk premium.

Each month we sort assets within an asset class based upon their annualized roll yield. We then form market neutral long/short portfolios which are long (short) relatively high (low) carry securities. Finally, to create our carry alternative risk premium we combine

[58] In the case of commodities and FX we use the average value for the previous 4½ to 5½ years to match the methodology of Asness *et al.* (2013).

the four asset class portfolios into one alternative risk premium, using equal volatility weighting.

5.4.2.3 Time Series Momentum

Although a long/short portfolio, the time series momentum portfolio differs from carry and value, in that it is not market neutral. The portfolio holds long positions in assets with positive momentum and short positions in assets with negative momentum. The portfolio is formed following Moskowitz *et al.* (2012) using a twelve month formation (look-back) period and a one calendar month return period. These are the most common definitions used in the literature (see, for example, Hurst *et al.* (2012) and Moskowitz *et al.* (2012)). The momentum signal is defined as

$$M_t^i = sign(\sum_{k=1}^{12} \log(1 + r_{t-k}^i)) \tag{5.5}$$

where, M_t^i is the momentum of instrument *i* at time *t* and r_{t-k}^i is the excess return of instrument *i* at time *t-k*.

A momentum portfolio is created for each asset class initially. Each instrument is given an equal dollar weighting within the asset class, before asset classes are combined using equal volatility weighting into one time series momentum alternative risk premium.[59]

5.4.2.4 Options Strategies

Our final alternative risk premium is the Fung and Hsieh (2001) options based trend following factor. We include this as an alternative risk premium for two reasons. First, it has consistently been shown to have high explanatory power out of sample for CTAs, in addition to other hedge fund strategies (Fung and Hsieh (2004)). Second, given a significant number of CTAs in our sample list "option strategies" as their primary category it seems plausible that the Fung and Hsieh (2001) alternative risk premia may also have high explanatory power for this group of CTAs. We expect a negative coefficient on the options premium for this group of CTAs as they tend to be short volatility. Fung and Hsieh (2004) model for diversified portfolios of hedge funds specifies three trend-following alternative risk premia, including Bond (*PTFSBD*), Currency (*PTFSFX*) and Commodity (*PTFSCOM*). To be consistent with our approach

[59] We equal dollar weight at the asset level to be consistent with our other alternative risk premia. Using equal risk weighting has no effect on our results.

for value, momentum and carry we also include an Equity Index trend-following alternative risk premia (*PTFSEQ*) in our analysis.

5.4.3 Alternative Risk Premia Performance

The value, carry and time series momentum alternative risk premia generate returns (Table 5.7, Panel A) of between 2.5% and 4.5% per annum, with Sharpe ratios ranging from 0.45 to 0.76. In contrast, the option alternative risk premium generates returns of -4.5% per annum, with a negative Sharpe ratio of -0.68. Though we use gross alternative risk premia returns for all of our analysis, for illustration Table 5.7, Panel B reports the returns for the alternative risk premia net of transaction costs, which have a small negative effect on performance, with Sharpe ratios now ranging from 0.41 to 0.74.[60]

Table 5.7
Alternative Risk Premia Summary Statistics: January 1994 to July 2015

The table presents summary statistics of the four alternative risk premia used in the analysis; value (VAL), carry (CAR), time series momentum (TSM) and options (OPT). Panel A presents their key performance statistics excluding trading costs; annual return, volatility and Sharpe ratio. Panel B shows the same analysis net of trading costs, with the exception of OPT where trading cost estimates are unavailable. In both Panels the annual excess return is the return in excess of the risk free rate. Panel C shows the cross correlations of the four alternative risk premia.

	VAL	CAR	TSM	OPT
Panel A: Alternative Risk Premia Returns				
Annual Excess Return (%)	2.60	4.14	4.59	-4.35
Volatility (%)	5.52	5.33	6.50	6.53
Sharpe Ratio	0.47	0.78	0.71	-0.67
Panel B: Alternative Risk Premia Returns, Net of Trading Costs				
Annual Excess Return (%)	2.37	4.02	4.39	-4.35
Volatility (%)	5.51	5.32	6.49	6.53
Sharpe Ratio	0.43	0.76	0.68	-0.67
Panel C: Alternative Risk Premia Correlations				
VAL	1.00	-0.27	-0.34	-0.03
CAR		1.00	0.00	-0.24
TSM			1.00	0.23
OPT				1.00

Cross correlations reported in Table 5.7, Panel C highlight the very different return characteristics of the alternative risk premia. Value has a negative relationship with the

[60] Futures transaction cost estimates are taken from Hutchinson and O'Brien (2014). We do not have data on transaction costs for the options data.

remaining three alternative risk premia, whereas only time series momentum and options are positively correlated, unsurprising given the existing literature documents how the Fung and Hsieh (2001) alternative risk premia capture the return characteristics of trend followers, who pursue strategies related to time series momentum.

5.5 CTA Alternative Risk Premia Analysis

Next we combine our futures and options based alternative risk premia with our dataset of CTAs. We first examine the premia exposures and performance of the aggregate portfolios of funds before using our cluster styles, which are based upon how funds generate returns. Finally, we report results using self-classifications.

The general equation we estimate to compute a CTA portfolio's exposure to the alternative risk premia is:

$$r_{i,t} = \hat{\alpha}_i + \sum_{k=1}^{K} \hat{\beta}_k^i ARP_{k,t} + \hat{\varepsilon}_{i,t} \quad (5.6)$$

where $r_{i,t}$ is the net-of-fees excess return on CTA portfolio *i* at time *t*, $\hat{\alpha}_i$ is the estimated alpha of the CTA portfolio, $\hat{\beta}_k^i$ is the estimated alternative risk premia exposure of CTA portfolio *i* on alternative risk premia *k*, $ARP_{k,t}$ is the return of alternative risk premium *k* in month *t*, and $\hat{\varepsilon}_{i,t}$ is the estimated residual.

Table 5.8
CTA Alternative Risk Premia Exposure: January 1994 to July 2015

The table reports the results from a regression of the excess returns of CTA portfolios (both Equal Weighted and AUM Weighted) against four alternative risk premia; value (VAL), carry (CAR), time series momentum (TSM) and option (OPT). The regression coefficients along with their test statistics (in brackets) are shown. Coefficients significant at the 10% level are highlighted in bold.

	ALPHA	VAL	CAR	TSM	OPT	Adj. R^2
Equal Weighted Index	0.17	**0.0699**	**0.0903**	**0.2043**	**0.2368**	0.34
	(1.45)	(1.91)	(2.45)	(6.69)	(8.03)	
AUM Weighted Index	**0.32**	0.0296	**0.1064**	**0.2611**	**0.2382**	0.31
	(2.25)	(0.65)	(2.33)	(6.87)	(6.49)	

Our baseline results are reported in Table 5.8, where we report results for portfolios using all CTAs in our sample, formed using equal weighting and AUM weighting. For both portfolios three of the four alternative risk premia have a statistically significant positive relationship with CTA returns. In aggregate CTAs are positively related to carry, time series momentum and the options alternative risk premia. The explanatory power of the model is relatively low at 34% (equal weighted) and 31% (AUM weighted), leaving 66% and 69%, respectively, of returns unexplained by the alternative risk premia. While both portfolios generate positive alpha ranging from 17 to 32 basis points per month, the AUM weighted portfolio alpha is significant at statistically acceptable levels.

Having established that there is some statistically significant alpha earned by CTAs, albeit concentrated amongst the larger funds (AUM weighted portfolio), next we examine how that performance evolves over time. Figure 5.3 reports the results from estimating the alternative risk premia model using a rolling 60 month estimation period. Panel A (Panel B) presents the rolling alpha (t-statistic of alpha). The results indicate that there has been no deterioration in performance (alpha) over time and the t-statistic is in fact higher in recent periods, reflecting a lower standard error of the performance measure. Finally in Panel C we report the rolling adjusted R^2 which shows that there is considerable time series variation in the explanatory power of our four alternative risk premia models, ranging from 20% to 60%.

Figure 5.3
Time Varying Alpha: January 1994 to July 2015

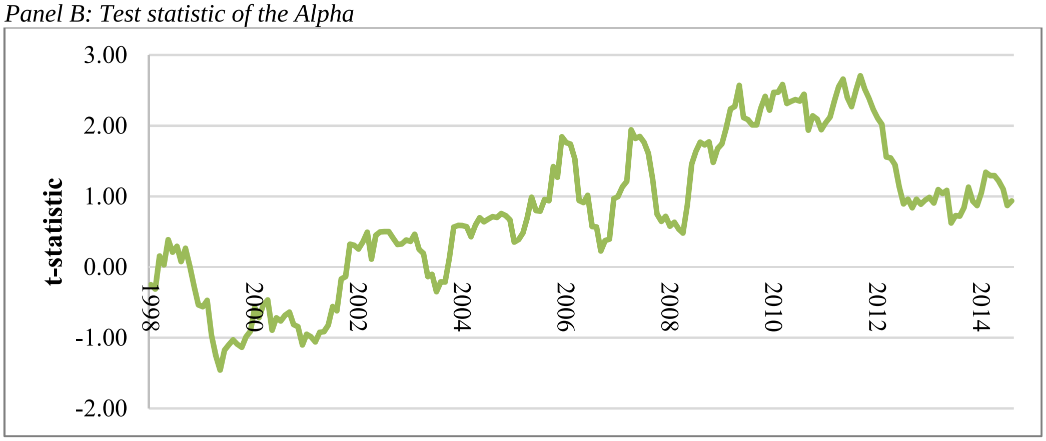
The figures show the results of regressing the excess return of an equal weighted index of CTA performance against the four alternative risk premia over a rolling 60 month window. The figures show the monthly risk adjusted return (Panel A), the test statistic of the risk adjusted return (Panel B) and the adjusted R^2 of the regression (Panel C).

Panel A: Alpha

Figure 5.3 - Continued
Time Varying Alpha: January 1994 to July 2015

The figures show the results of regressing the excess return of an equal weighted index of CTA performance against the four alternative risk premia over a rolling 60 month window. The figures show the monthly risk adjusted return (Panel A), the test statistic of the risk adjusted return (Panel B) and the adjusted R^2 of the regression (Panel C).

Panel B: Test statistic of the Alpha



Panel C: Adjusted R^2

5.5.1 CTAs and Alternative Risk Premia: Cluster Analysis

Next in Table 5.9 we present an analysis dividing the returns of CTA clusters into alternative risk premia exposure and alpha. Looking first at the equal weighted clusters (Panel A), the explanatory power of the models is modest with adjusted R^2 range from 14% to 44%. All of the clusters have a statistically significant relationship with at least one of the alternative risk premia. Longer Term Trend, Fundamental Value, Fundamental Carry and Option Strategies all have positive value exposure, while only Fundamental Diversified is negatively related to value. Fundamental Diversified, Fundamental Carry and Option Strategies are all positively related to carry, whereas Fundamental Value has a negative carry coefficient. The third alternative risk premium, time series momentum, is positively related to Diversified Trend, Longer Term Trend and Option Strategies. Perhaps unsurprising, given their well-documented explanatory power in the literature, the Fung and Hsieh (2001) options based alternative risk premium is related to all clusters, except Longer Term Trend and Fundamental Value. Coefficients are generally positive, with the exception of Option Strategies and Fundamental Diversified.[61] By creating these more homogenous clusters, we find that the explanatory power of the alternative risk premia is higher (relative to the full sample results) for the trend clusters, whereas it is relatively lower for the fundamental clusters. However, in absolute terms the explanatory power remains low.

Table 5.9

Alpha and Alternative Risk Premia Exposure of CTA Clusters: Jan. 1994 to July 2015

The table shows the results of regressing the average return of each of the eight clusters on four alternative risk premia; value (VAL), carry (CAR), time series momentum (TSM) and options (OPT). The table reports the monthly Alpha, the exposure to the alternative risk premia and the exclamatory power of the regression (adjusted R^2). Panel A reports the results for equally weighted returns and panel B for AUM weighted returns. Coefficients significant at the 10% level are highlighted in bold.

	ALPHA	**VAL**	**CAR**	**TSM**	**OPT**	**Adj. R^2**
Panel A: Equally Weighted Mean Cluster Returns						
Diversified Trend	**0.41**	0.1299	0.1686	**0.8521**	**0.9520**	0.44
	(2.05)	(1.04)	(1.34)	(8.15)	(9.43)	
Longer Term Trend	-0.02	**0.2533**	0.1066	**1.0690**	0.2016	0.27
	(-0.09)	(1.80)	(0.75)	(9.07)	(1.77)	
Shorter Term Trend	**0.56**	-0.0063	0.1516	0.1167	**0.9255**	0.28
	(2.93)	(-0.05)	(1.25)	(1.16)	(9.52)	
Fundamental Value	0.18	**0.6278**	**-0.6035**	-0.1327	0.0400	0.23
	(0.93)	(5.04)	(-4.82)	(-1.28)	(0.40)	
Fundamental Diversified	-0.05	**-0.2766**	**0.3958**	-0.1319	**-0.2356**	0.16
	(-0.33)	(-2.81)	(3.99)	(-1.60)	(-2.96)	
Fundamental Carry	0.17	**0.3294**	**0.4161**	-0.0278	**0.4165**	0.14
	(1.10)	(3.45)	(4.33)	(-0.35)	(5.41)	
Discretionary	**0.36**	-0.0939	0.0206	0.0175	**0.5128**	0.25
	(3.20)	(-1.30)	(0.28)	(0.29)	(8.82)	
Option Strategies: Short	**-0.60**	**0.2619**	**0.2386**	**0.2654**	**-0.7052**	0.19
	(-3.07)	(2.12)	(1.92)	(2.57)	(-7.07)	

Perhaps of more interest initially for an investor in CTAs is the alpha. While we urge caution in interpreting these results as outperformance, given the low explanatory power of the alternative risk premia, alpha is statistically significant and positive for three of the clusters, Diversified Trend, Shorter Term Trend and Discretionary, ranging from 36

[61] Given CTAs have different track record lengths it is possible that the characteristics of clusters vary through time. To investigate this we estimate clusters exposures in sub-sample periods. These results (available from the authors on request) are remarkably consistent. When we split the sample into two sub-periods we find that only five of the thirty two risk premia coefficients change sign between the periods.

to 56 basis points per month. Unsurprisingly, given the low raw returns of 1.33% per annum, the Option Strategies have a statistically significant negative risk adjusted return (60 basis points per month).[62]

Table 5.9 - Continued

Alpha and Alternative Risk Premia Exposure of CTA Clusters: Jan. 1994 to July 2015

The table shows the results of regressing the average return of each of the eight clusters on four alternative risk premia; value (VAL), carry (CAR), time series momentum (TSM) and options (OPT). The table reports the monthly Alpha, the exposure to the alternative risk premia and the exclamatory power of the regression (adjusted R^2). Panel A reports the results for equally weighted returns and panel B for AUM weighted returns. Coefficients significant at the 10% level are highlighted in bold.

	ALPHA	VAL	CAR	TSM	OPT	Adj. R^2
Panel B: AUM Weighted Mean Cluster Returns						
Diversified Trend	**0.42**	0.2166	**0.2945**	**0.9047**	**0.8660**	0.36
	(1.85)	(1.51)	(2.04)	(7.55)	(7.48)	
Longer Term Trend	0.14	0.0026	-0.1001	**0.3876**	**0.1710**	0.11
	(0.82)	(0.02)	(-0.95)	(4.41)	(2.02)	
Shorter Term Trend	**0.59**	-0.0150	0.0684	**0.1388**	**0.4842**	0.17
	(4.06)	(-0.16)	(0.73)	(1.79)	(6.47)	
Fundamental Value	0.16	**0.1932**	**-0.4173**	**-0.2277**	0.0419	0.16
	(1.15)	(2.13)	(-4.57)	(-3.00)	(0.57)	
Fundamental Diversified	-0.03	**-0.2673**	**0.2487**	-0.0471	**-0.3182**	0.10
	(-0.17)	(-2.39)	(2.21)	(-0.50)	(-3.53)	
Fundamental Carry	0.06	**0.2910**	**0.4257**	0.0087	**0.4378**	0.10
	(0.33)	(2.51)	(3.66)	(0.09)	(4.69)	
Discretionary	**0.23**	**-0.1475**	-0.0603	0.0191	**0.2313**	0.10
	(2.24)	(-2.28)	(-0.93)	(0.35)	(4.44)	
Option Strategies: Short	**-0.44**	**0.2169**	0.1784	0.0857	**-0.3954**	0.09
	(-2.59)	(1.99)	(1.63)	(0.94)	(-4.50)	

5.5.2 CTAs and Alternative Risk Premia: Self-classifications

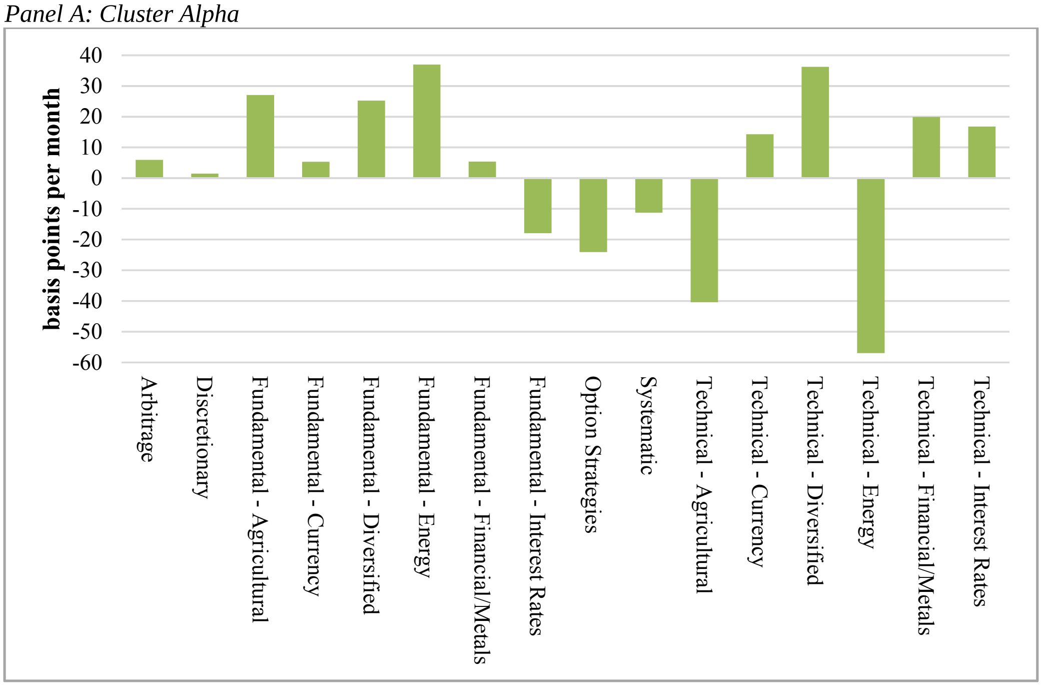
As noted in the data section our clustering technique requires a minimum of twelve months of returns. As removing funds with fewer than twelve months of data eliminates 950 funds and upward biases the average returns of the sample used in the clustering results by 0.035% per month, to ensure the robustness of our findings we report results based upon self-classifications in Figure 5.4.

[62] Though the explanatory power of the models tends to be lower, alternative risk premia exposures and alphas in Panel B are broadly similar for the portfolios weighted by AUM.

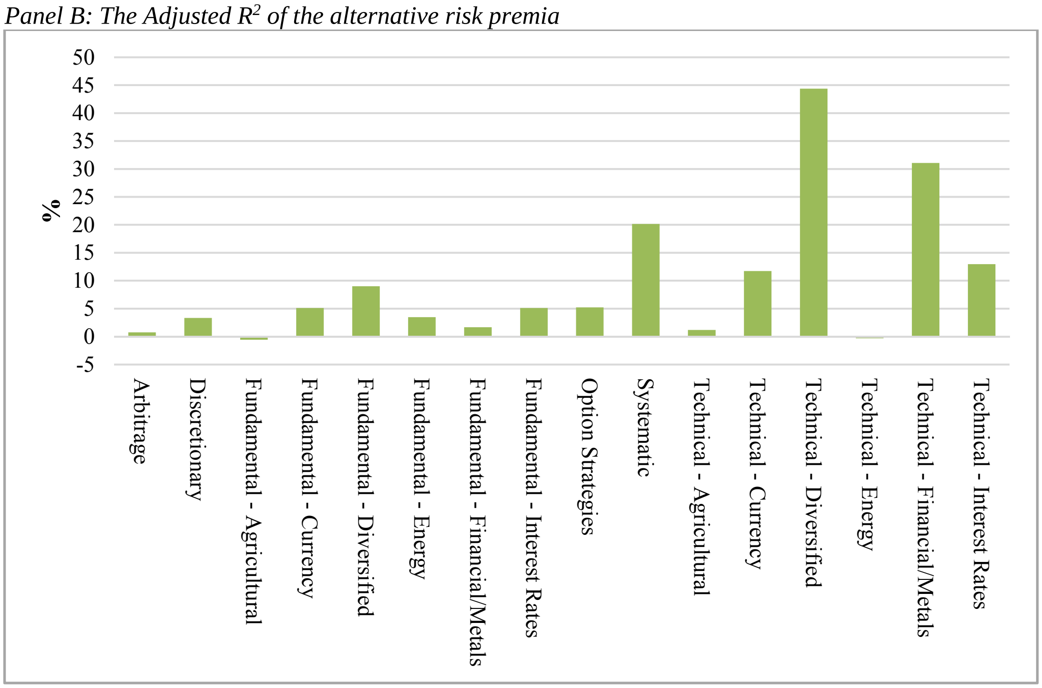
Figure 5.4
The Alpha of Self-classified Clusters

The figure reports the alpha of an equal weighted index of each of the twenty self-allocated classes (Panel A) and the power of the alternative risk premia to explain the return of each CTA classification (Panel B), defined as the adjusted R^2 of the regression.

Panel A: Cluster Alpha



Panel B: The Adjusted R^2 of the alternative risk premia



In terms of the relative performance of the different self-classifications of CTAs, in Figure 5.4 we report the alpha for each classification accompanied by the adjusted R^2

showing the explanatory power of the model. The best performing classifications are Fundamental-Agricultural, Technical-Diversified and Technical-Financials/Metals, whereas the worst performers are funds classified as Technical Agricultural and Technical Energy. In terms of explanatory power both Technical-Diversified and Technical-Financials/Metals are the highest at 44% and 32% respectively. CTAs do in some cases generate positive alpha, but it is notable that there is considerable cross sectional variation in model explanatory power, with the alternative risk premia explaining very little for some self-classifications.

Taken together the results presented in Section 5.5 suggest that the alternative risk premia factors specified in this paper are at best adequate in explaining the risk exposures of CTAs. With average explanatory power ranging from 14% to 44%, that leaves 86% and 56% respectively of CTA returns which are not coming from exposure to these alternative risk premia. This result demonstrates the challenge of specifying alternative risk premia to provide returns similar to CTAs.

5.6 Conclusions

This article was motivated by the observation that the future success of alternative risk premia products is dependent upon the assumption that they are able to adequately capture the returns of hedge fund strategies. While these products may offer advantages in terms of liquidity, transparency and fees, investors expect that they will produce hedge fund like performance.

Unfortunately, for a comprehensive sample of CTAs we find evidence to suggest the likelihood of these expectations being met is not high, primarily due to the heterogeneity in the sample. There are significant differences in the return characteristics of these funds. Using statistical clustering we find that three of our eight clusters (Diversified Trend, Shorter Term Trend and Longer Term Trend) have some correlation though they differ in exposures to alternative risk premia. There is also a clear category of funds which can be classified as Option strategies, due to their negative relationship with the option based factors. The remaining four categories which we class as Fundamental Value, Fundamental Carry, Fundamental Diversified and Discretionary have varying exposures (both in statistical significance and sign) to each of our alternative risk premia factors. To avoid introducing data snooping bias we limit our analysis to tradable alternative risk premia which have been published in the academic finance literature.

These simple alternative risk premia illustrate the difficult of modelling CTSA strategies. The low explanatory power of these alternative risk premia is striking. Between 56% and 86% of a cluster's returns are not explained by the alternative risk premia. Hence, developing products based upon these types of constructs with low tracking error to CTAs will be challenging.[63]

Looking at the portion of returns unexplained by the alternative risk premia, we find that on average CTAs historically generate positive alpha, though at marginal significance levels. Repeating the analysis focusing on within strategy self-classifications we find that Systematic-Diversified have historically offered the highest returns and performance. For portfolios of CTAs formed using statistical clustering our results demonstrate a lack of homogeneity amongst CTAs and reinforce our earlier finding that the category of funds with a high trend exposure (Diversified Trend) historically generated the highest performance.

Finally we note that, consistent with the literature, our analysis of the long term performance of CTAs, using the largest backfill and survivorship bias free dataset in the literature from January 1987 to July 2015, indicates that CTAs have generated consistently high performance through time. Sharpe ratios for the period January 1994 to July 2015 range from 0.37 (equal weighted) to 0.56 (AUM weighted).

The implications for investors are significant. Attempts to capture the returns of CTAs using alternative risk premia face challenges. CTAs are not a homogenous group therefore their returns are not easily characterised. Given the lack of a single identifiable style, developing products which seeks to track aggregate CTA performance using alternative risk premia will be difficult to implement. To illustrate this, we find recently published alternative risk premia represent a small proportion of the source of returns for the eight sub-strategies we identify within our CTA universe. Hence it is difficult to see these alternative risk premia being a close substitute for investing directly in CTAs.

[63] Our finding of low model explanatory power for CTAs is consistent with the empirical literature. For example, Kazemi and Li (2009) using a combination of sophisticated market, volatility timing and option based factors report maximum adjusted R^2 for discretionary (systematic) CTAs of 18% (53%).

Chapter Six

Robustness Tests

6 Robustness Tests

This chapter expands on discussions of methodology presented in the previous chapters. In particular, it tests the validity of three assumptions used in previous analysis.

Synthetic Futures: The methods used to create synthetic futures are discussed in detail. The validity of basing conclusions on analysis of synthetic rather than market price data is tested.

Transaction Cost Model: This chapter surveys the literature to provide evidence on level transaction costs to test the cost model used in creating the time series momentum portfolios.

CTA Fee Structure: The core purpose of this section is to test the assumption that CTAs generally charge a management fee of 2% and incentive (performance) fee of 20%. In addition, the trends over time in the structure of fees is presented.

6.1 Synthetic Futures

The use of synthetic future returns is common in studies of future trading across equity indices, government bonds and foreign currencies. They are used to increase the number of instruments in a study (Asness *et al.* (2013) and Koijen *et al.* (2013)) or extend the time frame (Moskowitz *et al.* (2012) and Hurst *et al.* (2012)).

6.1.1 Methodology

6.1.1.1 Synthetic Price Returns

The general methodology used to create a return series is described in previous chapters[64]. This focuses on calculating the excess return of an instrument in a given month. The excess return on a future contract is the sum of capital gain and income less the cost of funding the investment. Assuming the income and risk free rates are known and continuous at the start of a month, the formula is

$$er_t = (1 + r_t)\left(\frac{1 + q}{1 + r_t}\right)^{(1/12)} - 1 \tag{6.1}$$

where r_t is the return on the underlying spot instrument for the month, r_f is the one month risk free rate and q is the annualized yield. While this method can be applied in

[64] See Sections 3.1.2.1, 4.3.1.2 and 5.4.1

theory across all asset classes, the nature of the different asset classes and available data results in idiosyncrasies in the methodology across asset classes, these are discussed individually below.

6.1.1.2 Test Methodology

The tests in this section are based on comparison of the returns of two sets of portfolios generated from the same instruments and over the same time period and using the same trading rules. For each asset class, two sets of time series momentum portfolios are created, one based on exchange traded data and the other based on corresponding synthetic data. The performance of these is compared to verify that synthetic price data provides a good proxy for market prices. The momentum portfolios are created using the standard methodology for this work. The signal is defined using a twelve month formation period, so

$$M_t^i = sign\left(\sum_{k=1}^{12} \log\left(1 + r_{t-k}^i\right)\right) \tag{6.2}$$

where M_t^i is the time series momentum signal for instrument *i* for period *t*. The analyses focus on two key features of the return series; cumulative return and monthly correlation.

6.1.2 Equity Index Futures

In equity index markets, synthetic future prices are generated from total return indices. As this combines both price return and income, Equation 6.1 can be rewritten as

$$er_t = \left(\frac{I_t^{TR}}{I_{t-1}^{TR}}\right)\left(\frac{1}{1 + r_f}\right)^{(1/12)} - 1 \tag{6.3}$$

where I_t^{TR} is the value of the total return index at time *t*. The risk free rate is defined as the one month inter-bank offer rate in the corresponding currency. Calculating the return series *ex-post* includes the implicit, but reasonable, assumption that the dividends paid during a month are known at the start of the month.

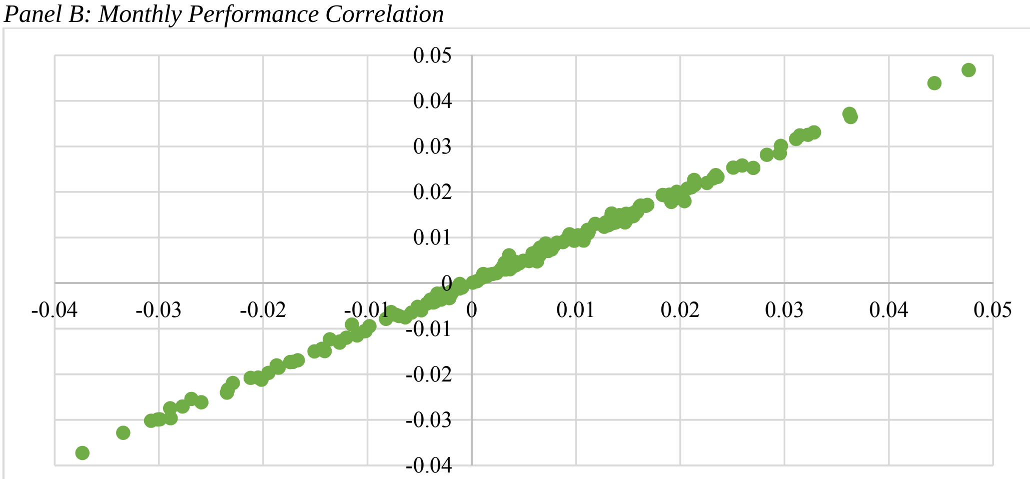
The portfolios are created on the basis of twelve national stock exchange indices. These are the set of indices which have an exchange traded future over the sample period, from 2000 to 2015 and sufficient data to calculate synthetic future prices.

The results are presented in Figure 6.1. There is no noticeable difference between the cumulative return series of the two portfolios (Panel A) and a high degree of correlation in the monthly returns (Panel B), with a correlation coefficient in excess of 99.9%.

Figure 6.1
Synthetic and Exchange Traded Futures Equity Index Portfolios: 2001-2015
The figures below compare the performance of two sets of portfolios generated from a time series momentum trading rule from January 2001 to September 2015. The first set is generated from the historic price data of twelve exchange traded future (ETF) contracts. The second is generated from synthetic future contracts for the corresponding instruments. The synthetic returns are created from total return indices and local risk free rates. Panel A shows the cumulative return of the two series and Panel B compares the monthly returns.

Panel A: Cumulative Performance

Panel B: Monthly Performance Correlation



6.1.3 Government Bonds

As with equity indices, synthetic return series for government bonds are created from total return indices. However unlike equity indices, there is no equivalent underlying asset. In general, future contracts are made up of a varying basket of bonds. The US basket comprises of US government bonds with maturities of six to ten years while the UK basket specifies nine to thirteen year maturities. The Australian government bond future is based on the 10 year interest rate and is cash settled[65]. The universe of futures is more limited than equities and the analysis is based on government bonds from six countries.

The synthetic return series are calculated from the total return index of a 10-year constant maturity government bond provided by DataStream, so that, as with equity indices, the excess return is defined as:

$$er_t = \left(\frac{I_t^{TR}}{I_{t-1}^{TR}}\right)\left(\frac{1}{1+r_f}\right)^{(1/12)} - 1 \tag{6.4}$$

where I_t^{TR} is the value of the total return index of the constant maturity bond at time *t*. The risk free rate is defined as the one month inter-bank offer rate in the corresponding currency.

The performances of the two portfolios are compared in Figure 6.2. Examining the cumulative return of the two portfolios (Panel A) shows differences between the two series, unsurprising given the mismatch between the instruments underlying the future contracts and those used to create the corresponding synthetic contracts. However, the general pattern is similar. The two series are correlated (Panel B) with a correlation coefficient of 96%. The volatility of the synthetic portfolio is higher than that of the exchange traded portfolio, consequently results based on this portfolio understate the Sharpe ratio relative to exchange traded futures.

6.1.4 Currency Futures

Synthetic currency futures were created for six currencies against the USD, based on the contracts available on the Chicago Mercantile Exchange (CME) from January 1999 to September 2015. The continuous return series was created by combining MSCI spot rates with the one month interbank offer rate for the USD and appropriate currency.

$$er_t = \left(\frac{S_t}{S_{t-1}}\right)\left(\frac{1+r_{t-1}^{f}}{1+r_{t-1}^{USD}}\right)^{(1/12)} - 1 \tag{6.5}$$

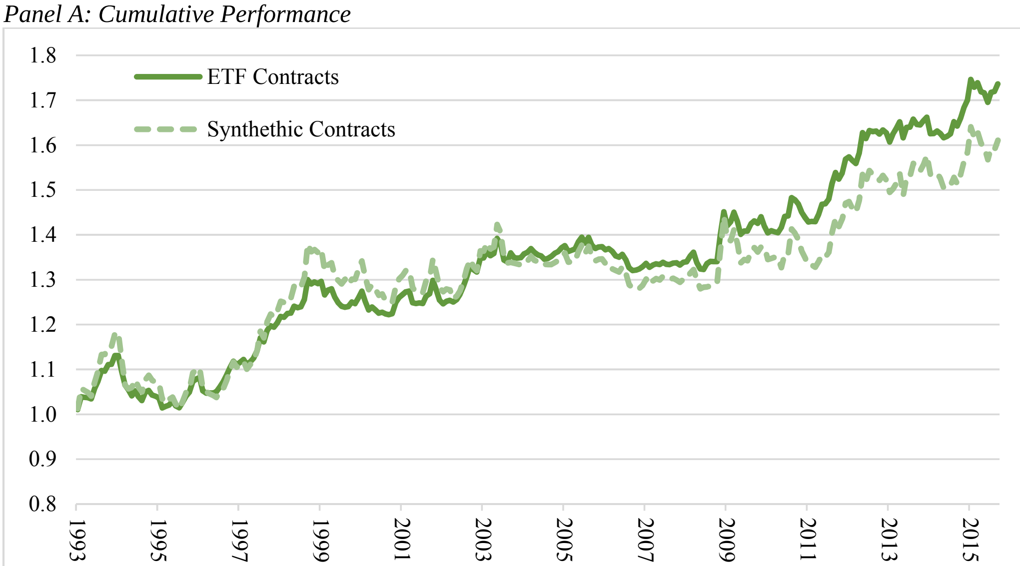
[65] The contract specifications were sourced from the websites of the Chicago Mercantile Exchange (www.cme.com), the Intercontinental Exchange (www.ice.com) and the Australian Stock Exchange (www.asx.com.au).

S_t is the spot price at time t, r_{t-1}^{USD} is the one month USD interbank offer rate and r_{t-1}^{f} is the one month interbank offer rate for the foreign (from the US point of view) currency. The formula respects the CME standard of quoting currency future prices as USD per foreign currency unit.

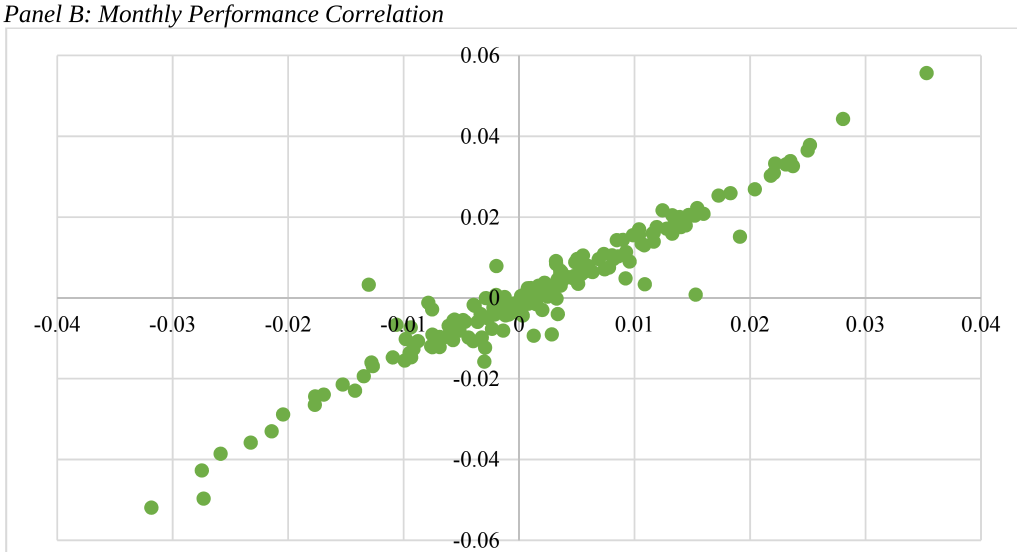
Figure 6.2
Synthetic and Exchange Traded Futures Government Bond Portfolios: 1993-2015

The figures below compare the performance of two sets of portfolios generated from a time series momentum trading rule from January 1993 to September 2015. The first set is generated from the historic price data of six exchange traded future (ETF) contracts. The second is generated from synthetic future contracts for the corresponding instruments. The synthetic returns are created from total return indices of 10-year constant maturity bonds and local risk free rates. Panel A shows the cumulative return of the two series and Panel B compares the monthly returns.

Panel A: Cumulative Performance



Panel B: Monthly Performance Correlation



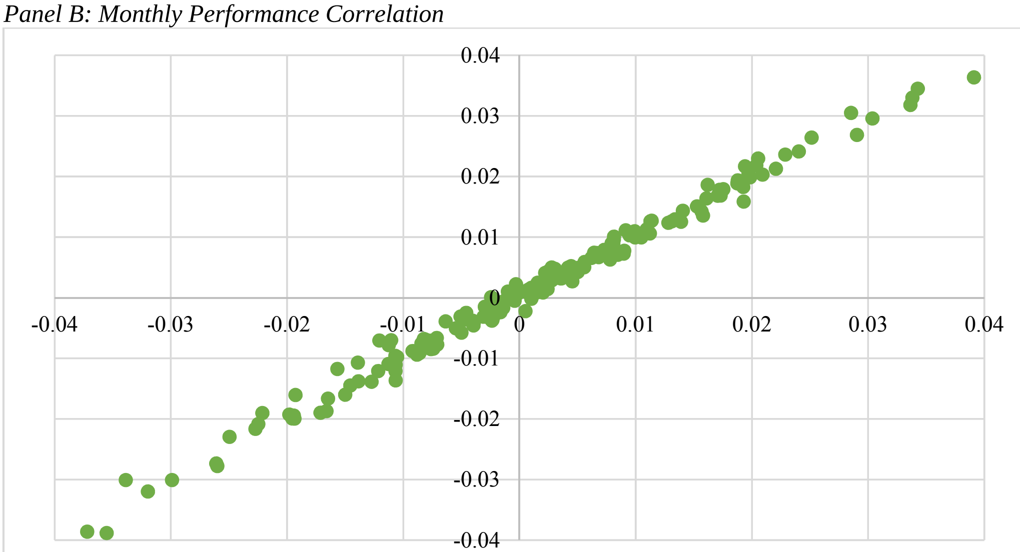
As in the case of equity indices, the spot price of the asset underlying the futures contract was available. Consequently the correlation between the return of each exchange traded future and its corresponding synthetic instrument is above 99.2% in all cases. The results of the two portfolios formed are shown in Figure 6.3. The cumulative return series (Panel A) of the portfolios are closely matched, however a minor drift in performance can be seen since 2008. The monthly return series have a correlation coefficient of 99.50%

Figure 6.3
Synthetic and Exchange Traded Futures Currency Portfolios: 2000-2015

The figures below compare the performance of two sets of portfolios generated from a time series momentum trading rule from January 2000 to September 2015. The first set is generated from the historic price data of six exchange traded future (ETF) contracts. The second is generated from synthetic future contracts for the corresponding instruments. The synthetic returns are created from the underlying spot price and risk free rates associated with each currency. Panel A shows the cumulative return of the two series and Panel B compares the monthly returns.

Panel A: Cumulative Performance

Panel B: Monthly Performance Correlation



6.1.5 Conclusions

The three analyses above compare, in three separate asset classes, the returns of time series momentum portfolios based on synthetic and exchange traded future data. In the case of both equity indices and currencies the returns of the portfolios are highly correlated. There is more variation between the bond portfolios due to the mismatch between the underlying instruments of futures contracts and the prices used to create the synthetic returns. However, the general pattern is similar and monthly correlations high over a twenty-three year period. The synthetic portfolio has a higher volatility and performance of this portfolio (based on Sharpe ratio) understates performance relative to the exchange traded portfolio. Taken together, the results give no reason to invalidate the assumption that inferences based synthetic products will replicate those based on exchange traded data.

6.2 Transaction Cost Model

The proper incorporation of transaction costs is essential to robust conclusions based on simulated trading strategies. Understating the magnitude of transaction costs can cause significant problems in both industry and academic settings. In industry, it can lead to overestimation of the profitability (or risk premium) of trading strategies and consequent overtrading, while in academic research, it can suggest anomalies to the efficient market hypothesis where none exist, Lesmond *et al.* (2004) assign the excess return of cross-sectional momentum to underestimated costs.

A transaction cost model, described by Hurst *et al.* (2012) and presented in Table 6.1, is used throughout this work to maintain the robustness of conclusions. This model defines transaction costs for a one way trade as a proportion of the nominal value traded and is a function of asset class and time. As a consequence, transaction costs for instruments within the same class are equal at any point in time. The model splits the time sample into three periods where costs are constant; up to 1992, from 1993 to 2002 and from 2003 on. The long period of constant costs in the first sub-period is based on analysis of transaction costs on the New York Stock Exchange presented in Jones (2002). This showed transaction costs remaining constant from 1930 to 1980, followed by a slow drift down from 1980 to 1990 and a significant reduction from 1990 to 1992. Hurst *et al.* (2012) calibrate the model by reference to one used by a large investment management firm.

Table 6.1
Transaction Cost Model

The table shows the transaction cost model used in creating simulated time series momentum portfolios. Costs are defined as a percentage of the notional amount traded for a one way trade.

	1900-1992	1993-2002	2003-2013
Equities	0.36%	0.12%	0.06%
Bonds	0.06%	0.02%	0.01%
Commodities	0.60%	0.20%	0.10%
Currencies	0.18%	0.06%	0.03%

Adapted from Hurst *et al.* (2012)

Table 6.2 demonstrates the effect of applying this cost model to simulated time series momentum portfolios with a twelve month formation period, showing the returns gross and net of transaction costs. Over the full period, transaction costs reduce the return from 19.18% to 15.81%, with a greater effect in earlier periods. Since 1992, transaction costs have fallen considerably and amount to less than 5% of gross profit. The magnitude of the costs relative to the gross return suggests that if the estimate used is reasonable it is sufficient to form the basis for reliable analysis and a detailed instrument specific set of models is not required.

The rest of this section focuses on verifying that the transaction cost model is reasonable. Before discussion of the evidence the general methods used to estimate transaction costs is discussed. The bid-offer spread is a key measure of transaction cost used in the literature. An investor can buy an asset at the offer price and sell at the bid price to complete a round trip trade. The long period of constant trading costs implied by the model is largely based on the finding that spreads remained constant over this period (Jones (2002)). Commission may (see, for example, Szakmary *et al.* (2010)) or may not (see, for example, Burnside *et al.* (2006)) be included. Following the literature, transaction costs can be estimated as:

$$TC = \frac{C}{V} + \frac{1}{2}.\frac{(P_{offer} - P_{bid})}{P_{offer}} \tag{6.6}$$

TC is the transaction cost, expressed as a fraction of the nominal value, consistent with the cost model used. P_{bid} *and* P_{offer} are the bid and offer prices respectively, C is the commission charged and V is the nominal value of the trade. Tick size, the smallest allowed price movement, is often used as a proxy for spread on commodity exchanges

(Szakmary *et al.* (2010)). Locke and Venkatesh (1997) note that transactions can occur within the spread, indicating spread based models can overstate costs.

Table 6.2
The Effect of Transaction Costs on Simulated Portfolio Performance

The table reports the average annual return of a twelve month time series momentum portfolio gross and net of costs. The results are reported for the full period and broken into three sub-periods, consistent with the three price levels in the transaction cost model. Results are expressed as an average annual percentage return.

		Diversified	Equity	Bond	Currency	Commodity
1950-2014	Gross Annual Ret.	19.18	5.87	5.80	2.32	3.11
	Net Annual Ret.	15.81	5.18	5.31	1.83	2.06
	Trading Cost	3.37	0.69	0.50	0.49	1.04
1950-1992	Gross Annual Ret.	20.64	5.91	6.21	2.72	3.13
	Net Annual Ret.	15.91	4.95	5.52	1.88	1.68
	Trading Cost	4.72	0.97	0.69	0.84	1.45
1993-2002	Gross Annual Ret.	22.68	5.81	6.86	4.13	4.55
	Net Annual Ret.	21.63	5.59	6.74	3.91	4.19
	Trading Cost	1.05	0.22	0.12	0.22	0.36
2003-2014	Gross Annual Ret.	11.24	5.79	3.43	0.13	1.80
	Net Annual Ret.	10.71	5.70	3.33	0.01	1.62
	Trading Cost	0.53	0.09	0.10	0.12	0.18

The evidence for changes in the relative level of trading costs through time is first discussed to verify key turning points in the cost function. Barclay *et al.* (1999) show that spreads fell by 30% when the NASDAQ was forced by the SEC to move from a quote based system to an auction system. Aitken *et al.* (2004) investigate the effect of the introduction of electronic trading on three specific exchanges in the late nineties and find that electronic trading results in a reduced bid-ask spread and consequently reduced trading costs. The general fall in transaction costs reflected in the model can be seen across a number of other asset classes. Subrahmanyam (2007) shows that spreads on individual equities in US stock markets and REITS both fall by over 80% from 1988 to 2002, while Marcato and Ward (2007) show the spread on US REITS drops by 75% from 1993 to 1995, remaining constant after that (to 2005).

Finally, evidence for the level of transaction costs from the literature is presented and compared with the levels indicated by our transaction cost model[66]. Burnside *et al.*

[66] Evidence on transaction costs is prevented in a variety of ways, and may be either explicit or implicit. Where necessary, the data from the literature is converted to a measure compatible with our cost model.

(2006) examine trading strategies in currency futures and includes data on spreads for the period 1976 to 2005 and the sub-period 1999 to 2005. The average of the bid-ask spreads of four currencies against GBP (one month forward) is 21 basis points, equivalent to 10.5 basis points transaction cost per one-way transaction. The time weighted average of our model is 12.5 basis points over the same period. The average implied transaction cost for the period 1999 to 2005 is 3.3 basis points, compared with the model value of 4.5 basis points. Finally, the average spread falls by 65% between these two periods, consistent with the model estimate of 67%. While these figures are consistent with the transaction cost model used in this work, it should be noted that evidence also demonstrates significant heterogeneity across the different currency pairs which is not reflected in the model used in this work and the relationship between trade size and spread is ignored.

Stevenson and Bear (1970) implement a trading strategy on Corn and Soybean futures from 1957 to 1968, their results implying a trading cost in the range of 25 to 35 basis points. Lukac *et al.* (1988a) use a standard cost of 100 USD per contract in their analysis of technical trading systems, indicating transaction costs in the same 25 to 35 basis point range for commodities and 2.7 to 4.0 basis points for currency futures. Over the same period the cost model estimates 60 basis point for commodities and 18 basis points for currencies Smidt (1965) uses a lower figure of 18 USD per contract for the period 1952 to 1961, this represents a significantly lower estimate of transaction costs than recorded elsewhere in the literature or suggested by our cost model. Sweeney (1986) estimates transaction costs of 6 basis points for trading in foreign currency forwards between 1975 and 1980. Szakmary *et al.* (2010) estimate transaction costs as 10 USD commission plus the minimum spread for a series of commodity futures. Converting this to a measure consistent with our model suggests transaction costs in the range of 3 to 6 basis points, about half the level of the model used here.

In general, the transaction costs reported explicitly or implicitly in the survey of papers investigating trading strategies are close to or below the levels suggested by the cost model. In addition, the key turning points and different relative levels of costs indicated by the model are consistent with those reported in the literature. Taken together, the evidence suggests the model provides a reasonable, possibly slightly conservative, estimate of transaction costs.

6.3 CTA Fee Structure

CTAs typically charge both a management fee, a proportion of assets under management, and an incentive (performance) fee based on investment returns, typically assumed to be 2% and 20% respectively (see, for example, Hurst *et al.* (2012)).

The estimates of CTAs' fee structure in has significant impact on two important types of analysis. A fee structure must be assumed to convert the gross return of simulated trading strategies into net returns seen by investors and to estimate gross returns generated by CTAs trading strategies from results presented net of fees. The purpose of this section is to test the validity of assuming the 2% and 20% fee structure for these analyses. For convenience, this fee structure will be referred to as the standard structure.

The analyses presented here are based on the cleaned BarclayHedge CTA database used in Chapter 5 and described in Section 5.3.1. This database is further processed to remove funds that do not charge any fees and a small number of funds where there are clear errors in recording the fees[67].

The method used to record the fees in the database has a significant limitation that should be borne in mind when reviewing the analysis below. The fee data is stored as a static item rather than a time series; that is only one value is stored for each fund. As a consequence, there is no indication whether these fees are associated with the entry of the fund into the database, are continuously updated or represent the fees associated with the final entry into the database. In the absence of other information, the analyses below assume that fee levels are constant over the life of a fund.

6.3.1 Average Fees

The first set of analyses, presented in Table 6.3, looks at the simple averages across all funds. The mean management fee is 1.82% and the mean incentive fee is 20.24%. While the incentive fee is very close to its standard value, the average management fee appears a little lower. The total fees of each CTA is then compared to the standard fees. While half of the funds charged the standard fees, 14% had higher fees and 23% had lower. It is not possible to estimate the relative levels of the remaining 14% of funds as these are a function of gross performance. Finally, there are a small but significant proportions of

[67] These errors consist of the management fee and incentive fee being reversed.

funds that either don't charge a management fee (11%) or don't charge an incentive fee (2.4%).

Table 6.3
Summary of CTA Fee Levels 1987-2015

The table summarises the fee structures reported to BarclayHedge by CTAs in the period January 1987 to July 2015. Standard fees refers to a structure of 2% management fee and 20% incentive fee. Average management and incentive fees are first reported along with frequency of higher and lower overall fee structures. Finally, the proportion of funds charging specific levels of fees are reported. Results are not adjusted for assets under management or lifetime of the fund.

Average Fee (%)			Fee Structure (%)	
	Management	1.82	2% Management Fee	55.06
	Incentive	20.23	20% Incentive Fee	71.58
Relative Fees Levels (%)			No Management Fee	10.54
	Standard	48.92	No Incentive Fee	2.40
	Higher	14.03		
	Lower	23.93		

The most common fee structures are shown in Table 6.4. The standard model dominates, with half of CTAs using this structure. The next most common structure is 1% and 20%, with 7.79% of funds. The proportion of funds using other structures falls away quickly. The table highlights two general groups of fee structures which deviate from the standard structure. One group charges only an incentive fee, while the other charge the standard rate (20%) incentive fee and a lower, but non-zero, management fee.

Table 6.4
Common Fee Structures of Commodity Trading Advisors

The table shows the eight most common fee structures reported by CTAs as recorded in the Barclay CTA database. The total sample size is 3,378 funds.

Management Fee (%)	Incentive Fee (%)	Number of CTAs	Proportion of CTAs (%)
2.0	20	1,652	48.92
1.0	20	262	7.76
0.0	25	125	3.70
1.5	20	125	3.70
2.0	25	118	3.49
0.0	20	102	3.02
3.0	20	88	2.61
0.0	30	80	2.37

6.3.2 Fees and Volatility

This section investigates the characteristics of funds that have atypical fee structures. The analysis focuses on the two most common groups identified above; CTAs that charge the standard incentive fee but have a low management fee and funds that charge incentive fee only. The characteristics of these CTAs are compared to the corresponding values for CTAs with the standard fee structure. The analysis focuses on data from 1994 as prior to this there an insufficient number of CTAs in the database to provide a reliable sample size. Cross-sectional volatility is used as a proxy for the risk of each class of CTA. For each month, the cross-sectional standard deviation of each class of funds is normalised by dividing by the cross-sectional standard deviation of the standard fee funds. The relative volatility is defined as the average value of this measure. The results are presented in Table 6.5.

Table 6.5
Characteristics of Non-Standard Fee Structures

The table compares characteristics of CTAs with an atypical fee structure to those using the standard structure. Results are presented relative to those of the standard fee structure. All reported values are statistically different from those of standard fee CTAs at the 99% confidence level.

Fee Structure		Value (%)	Relative Value	Std. Error
Incentive Fee Only	Average Incentive Fee	25.57	1.28	0.02
Incentive Fee Only	Relative Volatility		1.38	0.03
Low Management Fee	Relative Volatility		0.78	0.02

Looking first at the incentive fee only CTAs, these funds charge a significantly higher average incentive fee, 25.57% and have 28% higher volatility. In contrast to this, funds that charge a lower management fee have an average volatility level statistically significantly below standard funds.

In the case of funds charging incentive fee only, the results are consistent with those funds compensating for the lack of a management fee by charging a higher incentive fee and running riskier portfolios. While in the case of CTAs that charge lower management fee, this fee level is consistent with a model where investors are compensated with lower management fees by funds running at lower risk levels.

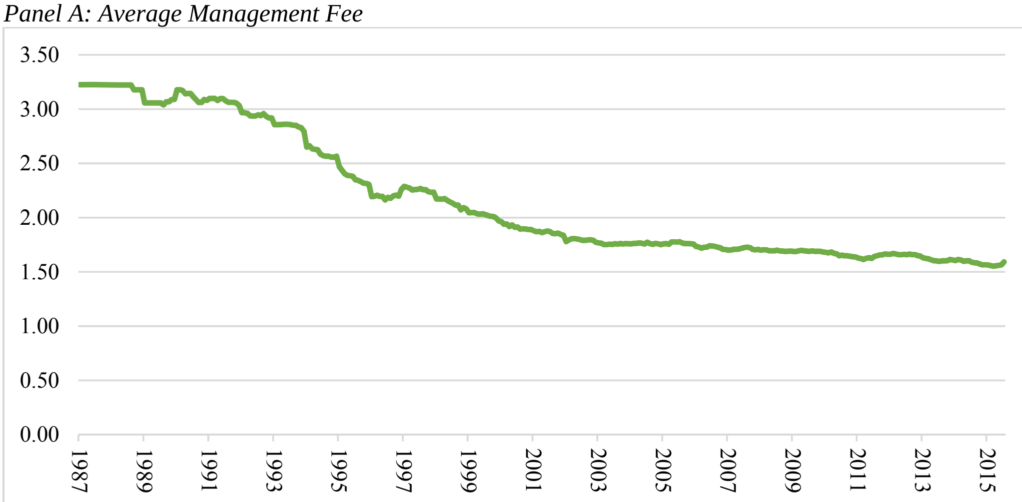
6.3.3 Trends in Fees

The final analysis in this section focuses on the trends in fees over time. The mean fee (management and incentive) is calculated for each month as the mean fee of all funds reporting returns in that month. The results are shown in Figure 6.6 with management and incentive fees reported in Panels A and B respectively.

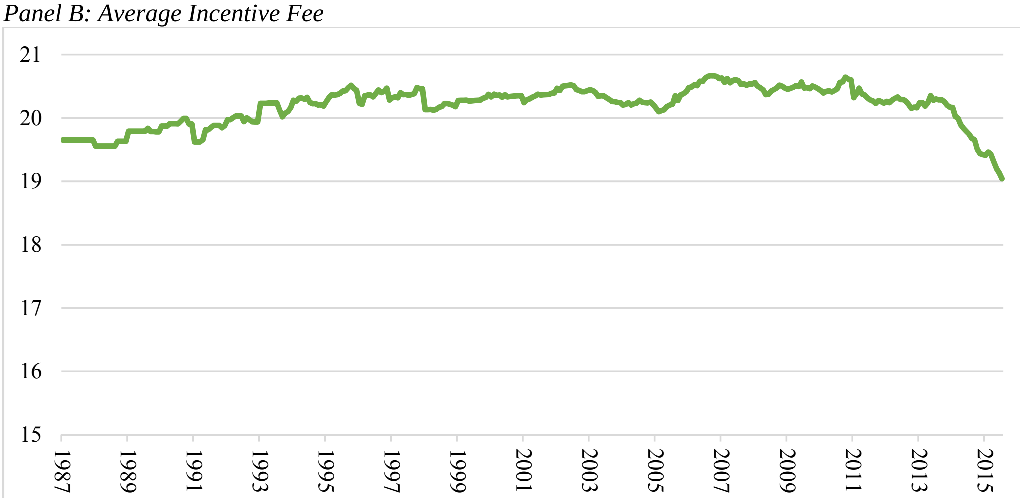
Figure 6.6
Trends in CTA Fees

The figures show the trend over time of the average management fee (Panel A) and average incentive fee (Panel B) reported by CTAs to BarclayHedge from January 1987 to July 2015. The average value of the management (incentive) fee in a given month is the unweighted average of the management (incentive) fee of all CTAs reporting a return in that month.

Panel A: Average Management Fee



Panel B: Average Incentive Fee



The management fee (Panel A) has shown a downward trend over time, falling from 3.2% to 1.6% over the sample period. The bulk of this fall was in the first half of the period from 1987 to 2002, since then the decline has been slower. The pattern is consistent with Peltz (1997) who reports average management fees of 2.5% and Irwin *et al.* (1993) who quote 2.5% for institutional investors and 5% for private investors. Both sources suggest an average level of incentive fees close to 20%

In contrast, the incentive fee (Panel B) has remain constant over the entire period, staying within a narrow band between 20 and 21% over most of the sample. It has fallen to 19% since 2014, but it is too early to place any significance on this.

The last analysis, Figure 6.7, investigates the trends in fee structure over time. Panel A divides CTAs into three categories depending on relative fee structure, standard, higher and lower and shows the proportion of CTAs in each category over time. CTAs where the fee level relative to the standard rate depends on the gross return are included in the calculations but not shown. Panels B and C show the trends in the proportion of CTAs reporting different levels of management and incentive fees respectively.

A long-term downward trend in totals fees is apparent in Panel A. Excluding funds with indeterminate fee structures, the industry has moved from a situation where 95% of CTAs charged the standard rate or higher in 1987 to one where 95% of CTAs charge the standard rate or lower in 2015. In effect, the standard rate has gone from being a lower bound to being an upper bound on fee levels.

The standard fee of 2% is the most common, with over 50% of the CTAs implementing this level of management fee since 1999 (Panel B). In the first quarter of the sample period higher management fees dominate, with over 60% of fund charging above 2% (the highest level was 6%, reported by 34 CTAs). Since then the proportion charging relatively high fees has consistently fallen to its current level of 3%. The proportion of funds with management fees below 2% has followed the opposite trajectory rising steadily from 4% to 35% throughout the period.

The 20% fee is the dominant level of the incentive fee, the majority of funds report a 20% management fee since 1994, and it has remained in a range between 70 and 80% since 1999 (Panel C). Unlike management fees, there is a consistent reduction in the proportion of funds that charge either higher or lower levels of incentive fee. It is finally worth highlighting a small but growing proportion of funds appearing over the last five years that do not charge an incentive fee.

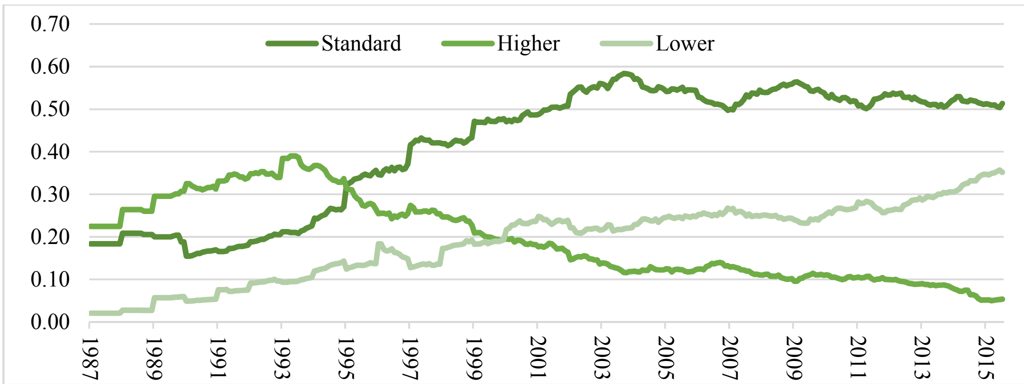
6.3.4 Conclusion

Over the full period the average fee levels were measured at 1.82% (management) and 20.2% (incentive) close to and not significantly different from the standard level. In addition, 50% of CTAs apply the standard fee structure and it is the most common structure by a considerable margin. These results justify the assumption of 2% management fee and 20% incentive fee and indicate that analysis incorporating results based on this structure are reasonable.

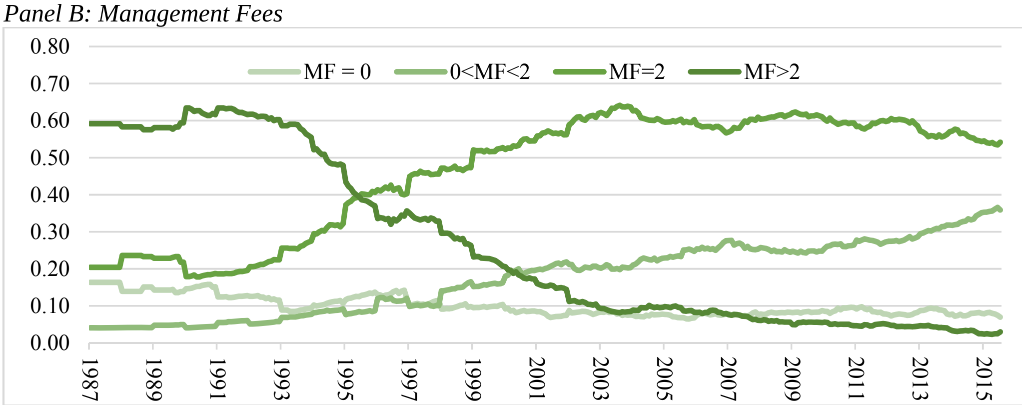
Figure 6.7
Evolution of CTA Fee Structures

The figure shows the trend over time in the proportion of CTAs using different fee structures in the BarclayHedge CTA database from January 1987 to July 2015. The CTAs are classified as equal to, higher or lower than the standard structure. The results are displayed for total fee levels (Panel A), management fee (Panel B) and incentive fee (Panel C).

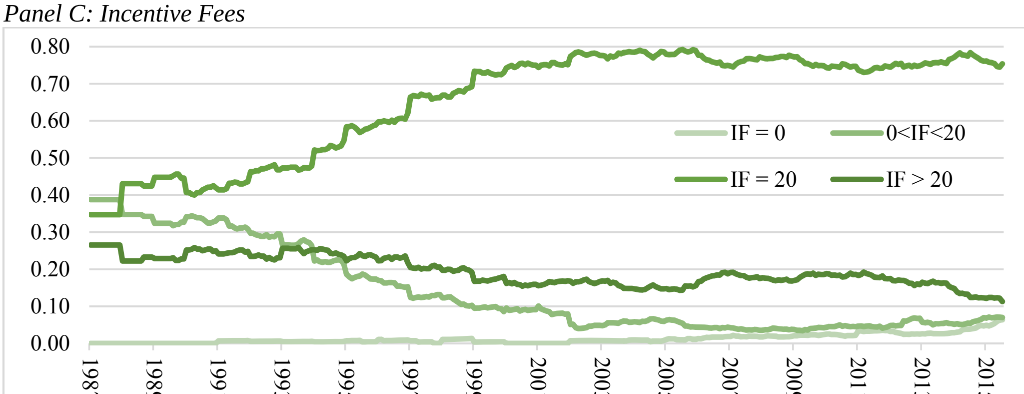
Panel A: Fee Levels



Panel B: Management Fees



Panel C: Incentive Fees



Funds with atypical management fee structures also have atypical performance profiles. The results are consistent with CTAs charging lower management fee as compensation to investors for running lower risk and running higher risk to compensate absence of management fees.

Looking at the two fees individually, the mean incentive fee has remained flat over the entire period, and continues to be close to 20%, while the mean management fee has a distinct downward trend over the period, researchers may wish to allow for this time variation in some studies. The growing number of funds that do not charge an incentive fee appearing in recent years may reflect the recent fashion for alternative beta funds.

Chapter Seven

Conclusions

7. Conclusions

This chapter draws together the key findings generated by the research presented in this thesis. The evidence on the effectiveness of time series momentum as a trading strategy is first assessed. This includes a discussion of both the conclusions on long-term performance and the robustness of those conclusions in the light of the methodologies used.

The following two sections deal with the relationship between the performance of time series momentum and the macroeconomy. The first is a narrow discussion of the relationship between its performance profile and financial crises. This is followed by a more general examination of the links established between time series momentum and general macroeconomic factors, including business cycle, economic variables and economic uncertainty.

The key findings on the CTA industry, based on detailed analysis of the BarclayHedge database, are then presented. This includes discussion of long-term aggregate performance, trading strategies, and exposure to risk premia including time series momentum.

The chapter concludes by highlighting areas where the research indicates further work is required.

7.1 Performance

Analysis of the long-term return profile of time series momentum is a constant theme throughout the research. Overall the three papers generated return series running from January 1925 to July 2015[68]. In extending the performance record back to 1925, the analysis covers a longer time period than any peer reviewed work.

The performance time series are obtained by measuring the returns of simulated portfolios generated from a mechanical time series momentum trading rule. The portfolios are constructed from futures contracts across four major global asset classes; equity indices, government bonds (both from 1925), currencies (from 1973) and

[68] The sample periods are January, 1925 to June 2013, January 1950 to September, 2014 and January, 1987 to July, 2015 respectively for the three papers. The years from 1940 to1949 are excluded from the analysis due to concerns about quality of data and operation of the markets around world war two.

commodities (from 1951). The returns are measured for a diversified portfolio, holding assets from the four classes and four sub-portfolios, each holding assets from a single class.

The diversified portfolio produces a consistent stream of returns in excess of the risk free rate, with few extended periods of poor returns. These periods of poor performance are generally characterised by flat rather than significant negative returns. Over the period 1925 to 2013, it generated a Sharpe ratio of 1.5. Splitting the sample into sub-periods highlights the consistency in returns, with Sharpe ratios of 1.3 and 1.2 for the periods 1950 to 1979 and 1980 to 2014 respectively.

The effect is replicated in the four major asset classes individually. A positive excess return is observed in each of the asset class specific portfolios. In the period up to 2014, the Sharpe ratios for the four sub-classes are measured at 0.96 (equity indices, from 1950), 0.83 (government bonds, from 1950), 0.41 (foreign currencies, from 1972) and 0.49 (commodities, from 1951).

The robustness of this conclusion is a function of the methodology used to generate the return series. Three significant concerns with the methodology are identified and analysed; the use of synthetic rather than real price data, the proper incorporation of trading costs and the validity of using synthetic rather than exchange traded futures' data.

Failure to properly include transaction costs in simulated portfolios can make conclusions based on simulated returns unreliable, in particular under-estimating costs can lead to erroneous conclusions of excess return. Consequently, results presented in this research are net of transaction costs. The model used to estimate costs is verified through comparison with others in the literature and found to assume similar but slightly higher costs than typical, indicating the conclusions are robust to transaction costs. The use of a twelve month formation period limits the turnover of the portfolio and consequently reduces the stress on the cost model.

While exchange traded data is optimum, it is not possible to extend the track record back to 1925 based on this type of data alone. It is necessary to create synthetic future data; that is replicate future return series from the underlying spot and risk free rates. In consequence, the simulated portfolios are a combination of exchange traded and synthetic instruments.

Although this technique is widespread in academic literature, its validity is explicitly tested here. The tests focus on comparing the performance of two portfolios, one created from synthetic data and the other from corresponding exchange traded future data. High correlation between the portfolios indicates that synthetic data can be used as the basis for valid conclusion.

In a less formal approach to the same problem, a number of the analyses focus exclusively on the period after 1980, where portfolios were dominated by exchange traded futures. Time series momentum is found to produce a statistically significant excess return over this period.

Finally, analysis of CTA returns reported to the BarclayHedge database, discussed in greater detail below, confirms the excess returns observed in simulated portfolios have also been obtained in financial markets by CTAs running time series momentum strategies.

Taken together, these studies confirm that the primary conclusion of this section that time series return produces a consistent excess return is reliable.

The presence of returns to time series momentum is tested indirectly by detailed analysis of a key feature of financial markets linked to time series momentum, auto-correlation of asset prices (Moskowitz *et al.* (2012)). The evidence for its presence is extended, showing it to be a feature of financial markets back to 1925 and across all four asset classes individually. It is linked more conclusively with time series momentum by demonstrating a positive relationship between the presence of the correlation and strong performance of time series momentum. The presence of this auto-correlation at lags of up to twelve months justifies the use of a twelve-month formation period for the trading rules used to generate portfolios.

7.2 Financial Crises

The research establishes a link between the performance of time series momentum and financial crises. Six major global financial crises spanning the period from 1925 to 2013 are identified and, based on these, the sample period is split into crisis and non-crises periods.

The mean return to time series momentum in non-crisis periods exceed the performance in crisis periods by 11.5% per annum over the period 1925 to 2013. Using the shorter sample period 1980 to 2013, the difference ranges from 3.9% to 6.0% per annum depending on the definition of crises period. However, it can be noted that there is a lower average return in this periods. The same effect is seen in three of the four asset classes. Extended periods where no excess return is generated are identified in the aftermath of each crisis.

Two approaches are used to support the conclusion of a link between time series momentum and financial crises. A sample of eight regional crises from 1977 to 2000 are used as an out of sample test. Although the individual crises differ significantly with volatile return series due to the limited portfolio, the data set was limited to relevant equity indices, government bonds and currencies, in aggregate a pattern of poor performance followed by reversion to long-term norms is observed following financial crises. This replicates the return profile of the global crises.

Secondly, a change in the structure of markets in the period after financial crises is observed. Serial auto-correlation, associated with time series momentum, is observed at time horizons of up to twelve months. However, when markets are divided between crises and non-crisis periods, the relationship breaks down in the crisis periods. This effect is consistent across all four asset classes, emphasising the extent to which time series momentum is a feature of all markets.

These two tests strengthen the conclusion that there is a relationship between time series momentum and financial crises.

7.3 The Economy

Time series momentum produces excess returns in a variety of economic conditions; across the business cycle and in both rising (1950 to 1980) and falling (1981 to 2015) interest rate environments. However, a number of links were identified between the magnitude of this performance and macroeconomic conditions.

While the strategy has positive returns in both expansions and recessions, the returns vary with the business cycle. The average returns are statistically significantly higher in expansions relative to recessions. This result is robust to the definition of the business cycle; NBER, GDP data or interest rate spread, with differences of between 5% and 8% per annum, depending on the definition.

The link between time series momentum and the economy is investigated through the relationship between its return series and a set of economic variables previously shown to be important in explaining investment returns. While no relationships are found using linear models, some evidence of a conditional relationship is observed using the methodology of Chordia and Shivakumar (2002).

A further insight to the relationship between time series momentum and economic variables is obtained by decomposing the return series of individual assets into systematic and idiosyncratic components following the methodology of Grundy and Martin (2001). The systematic component of an asset's return is defined as that part of the return explained by its exposure to economic variables. Portfolios, and subsequently, return series were generated from a time series momentum rule based on each set of returns. In both cases, a diversified time series momentum portfolio generates a return statistically significantly above the risk free rate.

The return due to time varying exposure to these macroeconomic variables is about 40% of the total. This is consistent with part of the profitability of time series momentum being compatible with rational pricing models. A portion of the return can be explained as compensation for bearing time varying exposure to economic risk.

The same pattern is seen when the data is split into two sub-periods around the year 1980, with statistically significant excess returns generated by both portfolios in each of the sub-periods. It is noticeable that while the return of the systematic portfolio remains constant, there is a drop in the return to the idiosyncratic portfolio in the second period. While the significance of this should not be overstated, it may be a reflection of increased global correlation and represent a permanent fall in the efficacy of time series momentum.

A link between economic uncertainty (also referred to as macroeconomic risk) and time series momentum is demonstrated. The novel methodology developed by Bali *et al.* (2014) is used as the basis for a measure of economic uncertainty. This uncertainty index is extended back to 1950, co-incident with the earliest availability of monthly economic data series from the US. The analysis highlights an inverse relationship between the returns of time series momentum and economic uncertainty. The performance of time series momentum improves when economic uncertainty drops. Further this relationship remains statistically significant at lags of up to six months.

This supports the previous conclusion that time series momentum tends to perform below average following periods of financial crisis and changes in the business cycle. In addition, peaks in the value of the uncertainty index are coincident with the crises identified in the study of the links between time series momentum and financial crises, justifying their selection. The relationship between economic uncertainty and the performance of time series momentum provides a transmission mechanism linking changes in macroeconomic variables to changes in the performance profile of time series momentum following financial crises.

7.4 Commodity Trading Advisors

The performance characteristics of the CTA industry are explored through extensive analysis of the BarclayHedge CTA database. The database contains performance and other data on five thousand funds, subsequently reduced to a data set of three and a half thousand following a cleaning process to remove duplicated and backfilled data.

Backfill bias has been identified as a significant problem in assessing performance data from before 1994 (Fung and Hsieh (2000)). A new methodology, using records of index components, is developed to eliminate this bias. Applying this methodology to clean the BarclayHedge database extends the record of aggregate CTA returns back to 1987. This shows that over the period 1987 to 2015, the average aggregate excess return of CTAs is positive, with a Sharpe ratio of 0.38, net of fees. Further these returns are generated consistently throughout the period. Focusing specifically on the newly extended period, 1987 to 1993, both the aggregate returns and the volatility were higher than in subsequent periods. It should also be noted that allowing for fees, the gross return generated by the underlying strategies are significantly above those delivered by CTAs to investors and subsequently reported to the database.

In both industry and academic research, there is an assumption of a standard fee structure of 2% (management fee) and 20% (incentive fee). Analysis of the database shows that while this assumption is reasonable, there are some noticeable deviations, including significant cross section variation of fees. The average incentive fee remained constant around 2% over the period. There is a downward trend in the average management fee, which falls from 3.2% to 1.6% between 1987 and 2015. A general fall in fee levels is reflected in the fact that the standard structure has gone from being a floor on fee levels to a ceiling. The research also highlights that some of the variation in fee levels is explained by funds having atypical risk profiles.

Variations in performance profiles between different CTAs was investigated using statistical clustering. This allows eight distinct clusters to be identified objectively, each with a different return profile. Low correlation between the clusters emphasises the heterogeneity of the industry. In addition, comparison between the self-assigned classifications recorded in the database and the statistically derived clusters, shows that, as in the case of mutual funds (Brown and Goetzmann (1997)), self-classification is not a reliable guide to performance strategy for CTAs.

Four risk premia are used to identified the return strategies of CTAs; time series momentum, value, carry and options. The first three of these have been recently formalised and are shown to have generated significant risk premia over the period 1987 to 2015. The option factor is the widely used risk factor developed by Fung and Hsieh (2001). Each of the factors has explanatory power for the aggregate CTA performance index. In addition, when applied to the aggregate return series of the clusters, each of the factors has a statistically significant explanatory power for at least three of these.

Only three of the eight clusters (representing half of the funds) are exposed to time series momentum. CTAs cannot be dismissed as a homogenous collection of trend-followers. The clusters characterised as following time series momentum strategies generated the highest Sharpe ratios, further emphasising the extent to which excess return to the strategy observed in simulations has been realised in financial markets.

The portion of the returns explained by these risk premia is below 50% in all cases and falls as low as 14%. Clusters associated with trend following have the highest portion of their returns explained. This has significant implications for CTA investors. If CTAs are deliberately tracking these factors, apart from time series momentum, they are failing to capture a significant portion of available returns. In addition, the return drivers of the CTA industry are highly diverse and low cost replication of CTA performance through alternative risk premia funds is likely to have a high tracking error and unlikely to produce a reliable return stream.

7.5 Future Work

This study presents strong evidence for consistent long-term returns in excess of the risk free rate for trading strategies based on time series momentum. Despite some success in linking a portion of those returns to risk premia based on economic factors, the research does not focus on a theoretical explanation for the returns. In particular, it leaves open the question of whether the returns can be fully explained through other risk factors in the efficient market hypothesis – arbitrage pricing theory framework, are an anomaly in need of explanation or should be regarded as a potential risk factor.

This research has developed risk based explanations for part of the return of time series momentum through exposure to risk factors associated with the macroeconomy, both through time varying exposure to economic variables and through economic uncertainty. This indicates that some of the returns can be explained under the efficient markets hypothesis. Others have shown that a portion of the returns can be explained by alternative investment premia. However, in all cases, statistically significant returns above those associated with risk premia remain, explaining this potential anomaly to the efficient markets hypothesis provides motivation to further investigation of the phenomenon in the context of efficient markets, in particular whether it can be explained through additional risk factors or remains an anomaly.

Time series momentum is also under-represented in the literature on behavioural finance. The explanation of return continuations is a major theme in the literature but discussion focuses almost exclusively on cross-sectional momentum in equity markets. There has been little effort to apply behavioural theories to the observed time series momentum effect despite, *prima facia*, the compatibility of time series momentum and behavioural phenomena. There is a need for greater analysis of time series momentum under a behavioural framework.

In the absence of an explanation of the excess return through risk factors, consideration should be given to classifying the return as a risk premium. The return series to time series momentum is generated through the application of mechanical trading rules. This replicates the general methodology used to generate risk premia associated with recognised risk factors.

Variations of time series momentum has been long used in industry and investigated by academics, however the recent formal definition (Moskowitz *et al.* (2012)) has facilitated its study by creating a standard definition. A number of the findings in this research further assist this. Evidence for time series momentum, including both its performance and relationships between performance and other factors, is demonstrated consistently for all asset classes, indicating investigations should focus on global rather than market or asset specific answers to research questions. The evidence of links between time series momentum and auto-correlation in asset markets is further strengthened. While this in itself is not an explanation of time series momentum, it does provide alternative approaches to both investigating the effect and testing theories developed in the investigation.

The study of economic links is based on US economic variables and conditions due to the limited availability of international data. This is despite the fact that the assets forming the basis of time series momentum portfolios are global. As more data becomes available in the future, global data can replace US data in the economic models. In particular, it is necessary to test whether use of the global data, in theory a better fit for the portfolio, can explain a greater proportion of returns to time series momentum in a rational pricing framework.

The categorisation of all CTAs as trend-followers is an over-simplification. The investment class is heterogeneous, with about half of CTAs following some form of time series momentum based strategy. Links between four alternative risk premia and the returns of CTAs are established but the bulk of the returns remain unexplained. Further investigation is necessary to understand fully the return strategies used by this diverse collection of funds. The study highlights the low explanatory power of a number of risk premia, including value and carry, while also highlighting the significant risk premia associated with those factors. Taken together, these findings suggests that CTAs are either not directly targeting these risk premia or, if targeting them, failing to capture a large part of the available returns. Resolving this question can provide significant insights into the investment strategies of CTAs and their value to a diversified portfolio.

Chapter Eight

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8. Bibliography

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